The future of food supply in a constraining environment

Modelling the impact of trade, intensification, and cropland expansion on agricultural and environmental systems

D I S S E R T A T I O N

zur Erlangung des akademischen Grades

d o c t o r r e r u m a g r i c u l t u r a r u m
(Dr. rer. agr.)
im Fach Agrarökonomie

eingereicht an der
Landwirtschaftlich-Gärtnerischen Fakultät
Humboldt-Universität zu Berlin

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eingereicht am: 6. Juni 2012
Tag der mündlichen Prüfung: 12. Dezember 2012

Dedicated to

Karl-Josef Schmitz

Acknowledgements

Three years ago, I got the opportunity to start my PhD at the Potsdam Institute for Climate Impact Research (PIK). The work at PIK is characterized by interdisciplinary teamwork and "out of the box" thinking and I am very delighted to have benefited from this working environment. I am grateful to many people, who have supported me directly or indirectly during this time.

- First of all I want to thank my supervisor, Hermann Lotze-Campen, for his trust, support, and encouragement. I learned a lot throughout our many discussions about land use modelling but also enjoyed our regular down-to-earth chats about current agricultural topics.
- I thank Prof. Harald von Witzke for giving me the opportunity to be his PhD student at the Humboldt University Berlin. Furthermore, I thank Prof. Harald Grethe for agreeing to be one of the reviewers of this thesis.
- Jan Dietrich has been my closest colleague and friend at PIK. He went with me through the hard times of being a young scientist. Thank you for the many scientific and non-scientific discussions, your trust, and your clear thoughts.
- I am grateful to Benjamin Bodirsky for being a wonderful, chaotic, and kind-hearted roommate and friend.
- Big thanks to my "old" doctoral colleagues at the PIK land use group, Katharina Waha, Michael Krause, Isabelle Weindl, and Doreen Burdack and to the "new" members of our group. It is very inspiring to work in such a team.
- I want to thank our post-docs, Christoph Müller, Alexander Popp, Anne Biewald, and Susanne Rolinski for many open-minded and fruitful collaborations and your support.
- Thanks to Jörg Hurlin and Konstantin Hahlbrock for their open ears and creative minds throughout our many talks about my work and life in general.

My biggest debt of gratitude is owed to my entire family. Without their support, this thesis would not have been possible.

- I am grateful to my parents for giving me "roots" and "wings" and to Stephan and Ulrike for being great siblings and friends.
- A special thanks to my oldest supporter, who inspired me restless and taught me so many lessons about life. I dedicate the thesis to you.
- Finally, I am deeply indebted to Marion, who stands by me all the time, and to a little unborn marvel, which has fascinated and motivated us during the past months. I am sincerely grateful to take the future with you two.

Abstract

Agriculture plays a key role in the 21^{st} century, due to its importance regarding major challenges, like food security, poverty reduction, climate change mitigation, ecosystem service provision, water conservation, and bioenergy supply. One of the most prevailing questions in this context is how to provide enough food for a growing population under increasing environmental and climatic constraints. The demand for agricultural goods will rise in the coming decades, foremost due to population growth, higher incomes, increasing consumption of animal products and additional demand for bioenergy. At the same time, the potential for increasing agricultural production is highly uncertain. In this thesis, I will examine the most important processes behind higher food production, like intensification, cropland expansion, and international trade, and its interaction with the environment.

The processes are implemented in the global economic land use model MAgPIE ("Model of Agricultural Production and its Impact on the Environment"), which simulates spatially-explicit land use and land use change. Moreover, it examines procedures related to agricultural production, trade, production costs, greenhouse gas emissions, and water scarcity. Agricultural intensification is represented by endogenous technological change based on a measure of agricultural land use intensity and by improvements in irrigation agriculture. Both processes improve yields under additional costs and lead to lower pressure to expand cropland. The decision to expand cropland is based on the quality of converted land and the relative costs for expansion. Finally, international trade involves the potential to allocate the production more efficient and to save resources.

Results of the thesis reveal the importance of the interplay between intensification and cropland expansion. Countries in Africa, the Middle East and South and East Asia require high investments in technological change to cope with future demand. If forest area is protected against cropland expansion, investments in Pacific Asia, Latin America and especially Sub-Sahara Africa have to be further increased. Trade liberalisation lowers required yield improvements but leads to additional deforestation, especially in Latin America due to comparative advantages in agriculture. In terms of water scarcity, an opening of trade has foremost positive implications since water-scarce regions can save water through imports. This does not hold for Australia, Japan, and Central Asia, which additionally strain their water resources due to higher exports. Appropriate policies on international level can diminish the impact on environment and climate. The inclusion of avoided deforestation into a global emission trading scheme would be able to prevent deforestation. Similarly, policies reducing the consumption of animal products in developed countries would lower the pressure on water resources in water-scarce regions.

Four general conclusions are drawn from this thesis. First, future rates of technological change play a decisive role for meeting required demands and protect the environment. As a result, more domestic and international financial resources have to be allocated to the agricultural sector, foremost in Sub-Saharan Africa and South Asia. Second, increased trade liberalisation leads to higher economic benefits but partly at the expense of the climate and local environment, if no joint international regulations are put in place. Third, the interaction between local water scarcity and international demand needs higher political attention. Fourth, uncertainty in land use modelling is considerable and has to be addressed by science in terms of methodological advancements and novel communication approaches.

Zusammenfassung

Der landwirtschaftliche Sektor ist aufgrund seiner Bedeutung bezüglich Ernährungssicherung, Armutsreduzierung, Eindämmung des Klimawandels, Ökosystemdienstleistungen, Wassernutzung und Bioenergielieferung einer der Schlüsselsektoren des 21. Jahrhunderts. Eine der drängendsten Fragen ist in diesem Kontext die Sicherstellung der Ernährung einer wachsenden Weltbevölkerung unter Berücksichtigung zukünftiger klimatischer und umweltpolitischer Aspekte. Die Nachfrage nach landwirtschaftlichen Produkten wird in den kommenden Jahrzehnten aufgrund von Bevölkerungswachstum, höheren Einkommen, ansteigendem Fleischkonsum und Bioenergiegewinnung ansteigen. Gleichzeitig herrscht bezogen auf das Potential für die benötigte Steigerung der Nahrungsmittelproduktion große Unsicherheit. In dieser Doktorarbeit werden die wichtigsten, für eine höhere Nahrungsmittelproduktion erforderlichen Prozesse, wie Intensivierung, Flächenausdehnung und Handel, sowie deren Interaktionen mit der Umwelt näher untersucht.

Diese Prozesse fließen in das globale, ökonomische Landnutzungsmodell MAgPIE ("Model of Agricultural Production and its Impact on the Environment") ein. Das Modell simuliert räumlich expliziten Landnutzungswandel und untersucht damit verbundene Vorgänge und Einflüsse, wie die landwirtschaftliche Produktion, internationaler Handel, Produktionskosten, Emissionen und Wassermangel. Landwirtschaftliche Intensivierung wird durch endogenen technischen Fortschritt, basierend auf einem Maß für Landnutzungsintensität, sowie durch Verbesserungen der Bewässerungswirtschaft berücksichtigt. Beide Prozesse erhöhen die landwirtschaftlichen Erträge und führen zu einem geringeren Druck Ackerfläche auszudehnen, sind aber mit zusätzlichen Kosten verbunden. Die Entscheidung zur Flächenausdehnung hängt von der Qualität des umzuwandelnden Landes und den relativen Kosten der Umwandlung ab. Internationaler Handel ermöglicht eine effizientere Verteilung der Produktion mit dem Potential Ressourcen zu schonen.

Die Ergebnisse dieser Arbeit zeigen die Bedeutung des Wechselspiels zwischen Intensivierung und Flächenausdehnung. Regionen, wie Afrika, der Mittlere Osten, Südasien und China benötigen hohe Investitionen in technischen Fortschritt um der wachsenden Nachfrage standzuhalten. Diese Investitionen müssen vor allem in Sub-Sahara Afrika, Lateinamerika und dem Pazifischen Asien zusätzlich erhöht werden, wenn wertvolle Waldgebiete vor der Ausdehnung von Ackerland geschützt werden sollen. Zunehmende Handelsliberalisierung reduziert das Bedürfnis zur Produktivitätssteigerung mit Ausnahme von Lateinamerika, wo aufgrund komparativer Vorteile der Landwirtschaft höhere Produktivitätssteigerungen und stärkere Flächenausdehnungen beobachtet werden. Bezüglich drohenden Wassermangels hat eine Handelsöffnung in den meisten Fällen positive Auswirkungen, da wasserarme Regionen aufgrund vermehrter Importe Wasser sparen können. Dies trifft jedoch nicht auf Australien, Japan und Teile Zentralasiens zu, die durch erhöhte Exporte ihre knappen Wasserressourcen stärker beanspruchen. Angemessene politische Maßnahmen auf internationaler Ebene können die Auswirkungen auf Umwelt und Klima begrenzen. Die Einbindung von Regeln zum Waldschutz in einen globalen Emissionshandel könnte weitere Entwaldung verhindern. Gleichermaßen würde ein geringerer Konsum von tierischen Produkten in entwickelten Ländern zu einer geringeren Ausbeutung der Wasserressourcen in wasserknappen Gebieten führen.

Die Schlussfolgerungen der Arbeit können in vier Aussagen zusammengefasst werden. 1) Technischer Fortschritt in der Landwirtschaft spielt eine entscheiden-

de Rolle für das Erreichen zukünftiger Nahrungsmittelsicherheit bei gleichzeitigem Schutz der Umwelt. Um dies zu erzielen sind höhere nationale und internationale Investitionen in den landwirtschaftlichen Sektor, insbesondere in Sub-Sahara Afrika und Südasien, notwendig. 2) Zusätzliche Handelsliberalisierungen führen zwar zu wirtschaftlichen Vorteilen, aber bei fehlenden Restriktionen durch internationale Abkommen besteht die Gefahr, dass dies auf Kosten der Umwelt und des Klimas geschieht. 3) Wassermangel ist vor allem ein lokales Phänomen, welches aber durch internationale Nachfrage stark beeinflusst wird und daher höhere internationale Aufmerksamkeit bedarf. 4) In der Landnutzungsmodellierung auftretende Unsicherheiten sind zum Teil erheblich und sollten daher zukünftig durch methodische Weiterentwicklungen und neue Kommunikationsansätze stärker berücksichtigt werden.

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1 Introduction and overview

"Agriculture is our wisest pursuit, because it will in the end contribute most to real wealth, good morals, and happiness."

Letter from Thomas Jefferson to George Washington (1787)

1.1 Background and context

As market prices are an indication of scarcity, high food prices have been proven to be an alarming signal for society (Swinnen et al., 2011). Only for a small part of the world population food is an abundant good at any time and almost any price. For the other part, availability and related food prices are critical for life since they spend large parts of their income on food or make their living from farming (World Bank, 2007). Over a long period real food prices have steadily declined, leading to the general perception that the agricultural sector provides cheap food due to constantly declining production costs. As a consequence, agriculture has been increasingly neglected by politicians and society, and attention in developing as well as developed countries moved to industry and service sectors (de Janvry and Sadoulet, 2007). However, for around ten years average food prices have risen with considerable spikes in between (von Braun, 2007). The causes are manifold and are well summarized in Headey and Fan (2008). The authors argue that rises in oil prices and demand for biofuels have put the highest pressure on markets, resulting in a steady decline of stocks. Additional but weaker factors include rising demand in Asia, export restrictions, financial speculation, and weather shocks. The increasing prices resulted in political instabilities, which brought agriculture back on the global and national agenda; at least for a short time. Nonetheless, many of the underlying drivers will likely persist or even amplify throughout the 21st century. If current political and societal developments continue, the "perfect storm", as it was called by Josette Sheeran[1], is likely to be a rather perennial storm, than a one-time event. In the following, I will briefly elaborate on these drivers and outline the context in which this thesis is written.

[1] Josette Sheeran, Executive Director of the UN World Food Program, on 6 March 2008 (Ennis, 2008)

1.1.1 Food consumption: trends and uncertainties

Population growth as the basic driver behind food demand has been slowing down since half a century; from the peak of around 2% population growth per year in the late 1960s to 1.15% in recent years (United Nations, 2011). Regarding the future, projections about demographic developments are far from certain. Most official studies have overestimated fertility rate projections in the past (for a discussion, see Inoue and Yu (1979) and Duncan and Wilson (2004)). For instance, in 1994, the United Nations Population Division (UNPD), officially responsible for this task, forecasted the population in 2050 to be almost 10 billion, four years later, this figure was corrected to around 9 billion (United Nations, 1998). A recent report by the Club of Rome even expects the peak of population in 2042 with 8.1 billion people (Randers, 2012). It seems that the demographic transition[2] in developing countries will appear much faster than anticipated. However, heterogeneity on the globe is large and many developing countries will likely face a doubling of population until 2050 with associated increases in demand (PRB, 2011).

Besides population, income and the level of urbanisation are the most important factors determining future food demand. With both rising over time, first, per capita calorie intake rises and second, the composition of diets changes towards more fat and sugar consumption (Drewnowski and Popkin, 1997). As one result, plant calories are substituted by animal calories, which leads to increased demand for livestock products (Delgado, 2003). Through the refinement process of cereals and other feedstock to livestock products up to 90% of calories are lost on average (Godfray et al., 2010). Depending on livestock system and feedstock this has huge implications for land use and causes environmental externalities, like the emission of greenhouse gases or increased water stress.

In recent years, demand for non-food, especially bioenergy, has added a further pressure to the food equation. Emerging subsidies for bioenergy in the United States (US) and the European Union (EU) have led domestically and abroad to a surge of crop cultivation for first generation biofuels[3] (Banse et al., 2008; Hertel et al., 2010). Even though environmental and climate benefits are widely questioned (e.g. Fargione et al. (2008)), biofuel policies persist due to its decentralized nature and its attractiveness as rural development policy (Hochman et al., 2008). Moreover, although technologically largely uncertain, second generation biofuels open up possibilities for generating negative emissions (Rhodes and Keith, 2008), which possibly boost bioenergy production in the coming decades (Popp et al., 2011a).

Another demand category, not contributing to human nutrition, is food waste. While the exact amount is hard to ascertain, around 30 to 40% of produced food is wasted, both

[2]The demographic transition states that societies progress from a pre-modern regime of high fertility and high mortality to a post-modern one in which both are low. In the transition period, mortality rates decrease faster than fertility rates, leading to a growth in population (Kirk, 1996).

[3]Whereas first generation biofuels are based on traditional agricultural feedstocks, like cereals, sugar crops and oil crops, second generation biofuels are made from more sustainable sources, like biomass waste, tree crops and biomass growing on non-cropland area. The generation of second generation biofuels is still under development.

in developed as well as in developing countries (Godfray et al., 2010; Gustavson et al., 2011). Whereas developed countries squander most of it after processing at the household level, developing countries face the challenge of post-harvest losses at the farm and processing level. Insufficient storage and processing facilities are major causes (Parfitt et al., 2010). Eventually, by improving the conversion efficiency of used cropland to caloric intake through lower wastage, pressure on land and the environmental system can be significantly reduced (Smil, 2004).

1.1.2 Food production: potentials and limits

Despite large uncertainties about the supposable amount of future agricultural demand (Smil, 2000; Grethe et al., 2011), agricultural production has to be increased considerably within the next decades. For most of the time in history, cropland expansion was the main and often the only way to increase food production. Abundant land and the development of sedentary agriculture made it possible and necessary to follow this strategy. As a consequence, large parts of forests have been cleared and transformed to cropland, foremost in temperate zones (Williams, 1989). In contrast, today, in most regions land is the most limiting factor for agriculture (Rosenzweig et al., 1988), with large uncertainties about the remaining cropland potential. Hence, the main source of growth in the near past has been agricultural intensification with land saving technologies as its primary goal (Wik et al., 2008; van Meijl and van Tongeren, 1999).

Land use intensification, defined as an increase in land productivity (Netting, 1993; Kates et al., 1993), is largely triggered by public and private investments in the agricultural sector, foremost Research & Development (R&D) (Alston et al., 2009). As a result of hybrid breeding and an alteration of agricultural practices, crop yields have been increased significantly during the second half of the last century; predominantly in a linear way (Hafner, 2009). Although, scientific discussions about potential biological limits of yields are not without ambiguity, most studies conclude that those limits are not close (Reilly and Fuglie, 1998), and improvements in photosynthetic conversion efficiency would at least enable a doubling of yield potential (Zhu et al., 2010). Besides improving the maximum yield, possibilities to narrow the gap between average and maximum achievable yield are manifold. This holds especially for developing countries with an existing yield gap factor of 2 to 4 (Rockström et al., 2007).

Climate change puts additional uncertainty on future crop yields. On one hand, C3 crops will likely benefit from higher CO_2 concentration (Jaggard et al. (2010) estimates a 13% yield increase under 550 ppm CO_2 concentration). On the other hand, changing temperature and precipitation patterns will challenge and induce more instability to existing agricultural systems. Hereby, subtropical regions are generally negatively affected through increased droughts, whereas temperate regions on high latitudes would profit from higher temperatures (Easterling et al., 2007). However, complex biological processes and inscrutable feedback effects between plants and climate together with the variability coming from climate projections lead to considerable uncertainties about future climate impacts on crop yields (Müller, 2011). Besides impacted by climate change, agriculture and the land use sector also contributes around 32% to global greenhouse gas emissions with highest shares for CH_4 emissions from livestock production and N_2O emissions from fertilizer application (Stern et al., 2006). With a technical mitigation potential of around 6 Gt CO_2-eq.yr^{-1} agriculture could play an important role in terms of mitigation options in the future (Smith et al., 2008), although this sector is currently released of any mitigation duties.

Further regulations in the future could be related to soil degradation, deforestation, and water scarcity, as these are important externalities of agriculture. Between 16 and 40 % of global agricultural area is subject to light or severe soil degradation (Chappell and LaValle, 2011). Unclear property rights and missing knowledge about sustainable soil management practices enhance human induced degradation in developing countries. The main challenge is to increase soil carbon, which will not only cause higher yields, but could also be a viable climate change mitigation strategy (Lal, 2004). The same holds for avoiding deforestation, which is mainly caused by cropland expansion. Besides contributing significantly to worldwide greenhouse gases, it leads to socio-economic damages for the local population (Barraclough and Ghimire, 2000), reduced water cycling (Fearnside, 2005), increased flood risks (Bradshaw et al., 2007), disruptions of the local climate (Costa and Foley, 2010) and severe losses of biodiversity (Gorenflo and Brandon, 2005). Different kind of policy measures, like direct protection, inclusion of avoided deforestation in a global carbon market and compensation payments, are considered as viable options to protect tropical forests (Forner et al., 2006). Water scarcity is an another important externality, which is affected by agriculture, since more than 70% of fresh water use is attributed to irrigation agriculture (Gleick et al., 2009). The distribution of water scarcity around the world is very uneven. While most regions face no water scarcity nowadays and much likely not so in the future (most tropical and cold temperate regions), other regions face severe water stress (Central and South Asia, Middle East, North Africa and South-East Australia) (Vörösmarty et al., 2010). Strong heterogeneity in water scarcity and huge differences in the water content of different crops entailed the concept of virtual water trade. This concept promotes production of water-intensive products in water-abundant regions and its export to water-scarce regions (Oki and Kanae, 2004).

Finally, food production and its availability are largely dependent on socio-economic drivers, like energy prices and trade regulations. Costs of fossil fuel extraction have risen continuously in past decades and will likely continue in this manner, causing higher oil prices in the future (de Almeida and Silva, 2009). Increasing prices for oil affect agriculture in multiple ways, directly through higher diesel prices and indirectly through higher prices of energy-intensive inputs (fertilizer, pesticides and machinery). Hence, in the past a strong negative correlation between oil prices and agricultural production has been observed. In recent years, this relationship has been interfered by bioenergy production, leading to an improved integration of agricultural and energy markets (Schmidhuber, 2008). Energy prices also affect costs of international transports. Nevertheless, in the past, technological progress in the transport sector, reduced information costs and trade liberalisation efforts have largely outweighed risen energy costs and led to a tenfold increase in traded agricultural goods between 1955 and 2005 (FAOSTAT, 2010). International trade enables regions to specialize in their comparative advantages and allows equalizing production shocks in certain regions with imports from other regions. Hence, trade plays an important role for food security. On the other hand, individual trade regulations by countries can entail increased food prices and severe food scarcity in other regions, as observed in the recent crisis (Headey and Fan, 2008). Overall, the future of domestic and international trade policies appears to be crucial for fulfilling future demands, especially in situations of high food prices.

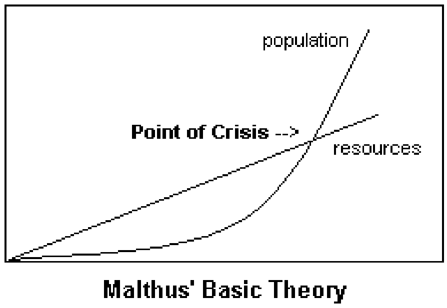
1.2 Historic analyses

The question of how mankind can feed itself has been one of the most prevailing questions of the past and present due to its importance and the uncertainty of answers (Smil, 2000; Federico, 2005). The most prominent person in history to approach this question, is probably Thomas Robert Malthus. With his famous book *"An Essay on the Principle of Population"* from 1798, he was the first who analysed the demography of past centuries and related them to a formal theory of the future (Malthus, 1798). He explained fluctuating populations by the rule that population increases exponentially but is limited by the linear increase of food production (Figure 1.2). His analysis of past developments is remarkable and almost entirely confirmed by the theory of secular cycles (Turchin and Nefedov, 2009). This theory describes how societies of the past have reached their carrying capacities, which led to crises and considerable declines in population.

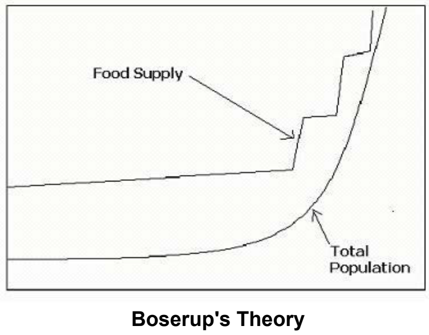
However, what Malthus could not know is that he wrote his analysis in the middle of an important revolution period and shortly before one of the most important scientific discoveries for agriculture: The invention of the steam machine initiated the industrial revolution and around 1840, Justus von Liebig discovered the use of nitrogen as fertilizer and its importance with the Law of the Minimum. Both happenings changed agriculture in the 19^{th} and 20^{th} century (Runge et al., 2003). As a consequence of Liebig's discovery all possible sources of natural nitrogen were used over time, leading to higher food production and world population[4]. The industrial revolution was responsible among many other developments for lower transport costs, increased trading activities and the mechanization of agriculture. Despite that, by the beginning of the 20^{th} century, limited availability of nitrogen created the need for alternatives to feed the growing population. The invention of the Haber-Bosch-Synthesis during the 1920s solved this problem and revolutionized agriculture by enabling the production of artificial nitrogen fertilizer (Smil, 2001; Hager, 2008). Another example for the adaptive capacity of the agricultural system is the rapid population growth in Asia after the Second World War. Together with strong income growth in some countries, food demand soared and fuelled the impression of a maximum carrying capacity. However, the introduction of semi-dwarf high-yielding grain varieties together with new management methods initiated the so-called "Green Revolution", which boosted agricultural production in the late 1960s and 1970s (Evenson and Gollin, 2003). In conclusion, it can be stated that Malthus

[4]For instance, in Germany, agricultural production increased by about 90% between 1870 and 1915 (Fesser, 2000)

did very well in describing the past, but failed in his outlook due to transmitting his historic analysis to future developments.



(a)



(b)

Figure 1.1: Graphical illustration of the theories by Malthus (Malthus, 1798) and Boserup (Boserup, 1965)

Esther Boserup addressed those developments and introduced a new theory published in the book *"The Conditions of Agricultural Growth: The Economics of Agrarian Change under Population Pressure"* (Boserup, 1965). She proclaimed almost the opposite. Whereas Malthus stated that population growth is limited by agricultural production, Boserup claimed that population growth triggers agricultural production (Figure 1.2). She summarized her theory with the expression *"Necessity is the mother of invention"*, prescribing that population pressure causes innovative solutions resulting in the intensification of agriculture (Turner and Fischer-Kowalski, 2010). Whereas, Malthus took the pessimistic view based on pre-industrial observations, Boserup defended the optimistic view mainly based on post-industrial studies. Since the 1970s, many scholars found arguments either for the optimistic (e.g. Simon (1981)) or the pessimistic view (e.g. Ehrlich (1968)). The Club of Rome presented 1972 the first piece of research, which tried to formalize the future outlook by using mathematical simulations (Meadows et al., 1972). With increasing computer power, this method is presently state-of-the-art in terms of simulating future developments. Still, as I argue in the next section, normative assumptions of either the optimistic or the pessimistic view will always be part of dynamic modelling.

1.3 Research approach

1.3.1 Modelling the future

Mathematical models are simplified and theoretical representations of reality. The main goal of modelling is to design and improve the model in order to reflect reality as best as possible. However, as reality is usually much more complex than a model and underlying data are able to handle, specific assumptions have to be taken. These simplifications are subject to biases and lead to uncertainties (Müller, 2011). Figure 1.2 illustrates in a simplified way, interactions between the theoretical and real world and the relations between problems (right side) and solutions (left side) (based on Ortlieb (2004)). The process starts with a real-world problem or a phenomenon which has to be explained. With modelling techniques this problem is transferred to a mathematical problem statement. Simulation analysis solves this problem in a mathematical way, after which the derived solution is interpreted regarding a possible solution in the real world. Finally, this solution is verified with the initial problem statement. This last step of verifying the model is not possible with dynamic models, looking into the future. The only option to validate the model would be to run past time steps and comparing the model results with observations. The first three steps are subject to simplifications and resulting uncertainties. As a consequence, underlying assumptions have to be communicated properly and put up for discussion.

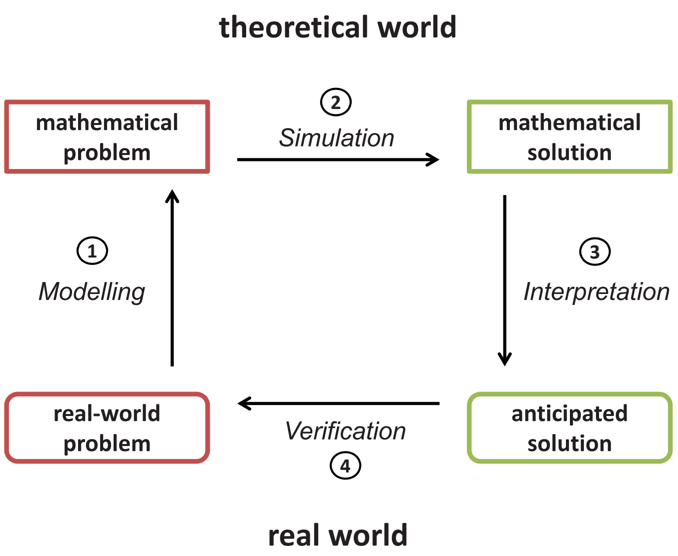


Figure 1.2: A model of the modelling process (own illustration based on (Ortlieb, 2004))

This all leads to a doubtful viewpoint of society regarding quantitative modelling of future developments. Most of the critique is caused due to poor documentation and communication of methods and assumptions as well as a general lack of transparency. On the other side, the request for concrete results and neglect of uncertainties by the society often leads to misinterpretations of model results, which spuriously lowers the trust in modelling methods further. These points have to be certainly considered by researchers involved in modelling. However, the general critique, implying that models have no important usage and do not give any benefit, has to be rebutted. According to Constanza and Ruth (1998), mathematical modelling is necessary since mental models are not sufficient to guide human's complex decisions, which are usually non-linear processes with spatial and temporal time lags.

I want to explain this with an illustrative metaphor: Having a model to explain future processes can be compared with having a road map before visiting a new city. Without a map, the searching person relies on explanations by different people about the streets in this city. This gives a first impression but does not picture the reality at all. A first drawing of the most important streets might help to orientate, an elaborated road map improves this image, and "Google Earth" probably gives the best formal impression before visiting this city. In the future, we might see further technologies to give a better impression of the city, but it will always stay an abstraction of real time.

The same holds for models simulating future developments. Without them, we only rely on mental exercises and personal appraisals. Those might not be wrong by definition but a model complements this by formalizing processes and revealing complex realities. The main difference between the map metaphor and modelling future developments lies mainly in the ability to validate. Since street maps picture the present, their quality can be verified quite easily. In contrast, future projections can only be validated ex post, which is problematic in case of long-term projections. Hence, scientists have to follow certain rules in order to build up trust and credibility. Those rules include transparency about applied methods and used data, application of sensitivity analyses, appropriate communication of results with regards to uncertainties and, finally, the continuous review of applied methods by comparisons and publications.

1.3.2 Economic land use modelling

> "Models of land use change are tools to support the analysis of the causes and consequences of land use changes in order to better understand the functioning of the land use system and to support land use planning and policy." Verburg et al. (2004), p. 309

The mission and purpose of land use models formulated in Verburg et al. (2004) can only be fulfilled if biophysical processes are combined with economic processes of land use change. Hence, biophysical vegetation models are missing the economic link, while agro-economic market models are lacking the spatially explicit biophysical modelling component. As a consequence, economic land use models emerged as a new class of models, filling the gap between economic equilibrium models and biophysical vegetation and hydrology models. An important feature of economic land use models is the connection of several different layers (e.g. global, regional and cellular layers) in order to capture and highlight important interactions (Figure 1.3).

Before the 1990s it was not possible to handle such large data sets and complex model equations to simulate future developments on a global scale with a fine spatially-explicit resolution. Since then, computing power has increased rapidly and software for handling data became available. However, the theoretical foundations on which the models are created are based on scientific knowledge build up over several decades. A groundbreaking step was Paul Samuelson's famous dissertation "Foundations of Economic

Figure 1.3: Different scales in economic land-use modelling at the example of MAgPIE

Analysis", which highlighted the importance of mathematics for economics (Samuelson, 1947). Most of the existing models are based on mathematical programming methods, which have been applied to economics (e.g. Dorfman et al. (1958) and Takayama (1985)) and later transferred to the agricultural sector (Hazell and Norton, 1988). The first large-scale optimization approaches on agro-economic modelling have been developed by Bruce McCarl from Texas University. Together with colleagues he developed the models ASM (U.S. Agricultural Sector Model) (Chang et al., 1992) and FASOM (Forest and Agricultural Sector Optimization Model) (Adams et al., 1996), which laid the foundation for many recent optimization models covering the agricultural sector.

One of those models is MAgPIE ("Model of Agricultural Production and its Impact on the Environment"), which is developed and managed at the Potsdam Institute for Climate Impact Research (PIK) (Lotze-Campen et al., 2008) and is the focus of this thesis. MAgPIE is a recursive dynamic land use model, meaning that the starting point of the current time step is based on the output of the previous time step. As a partial equilibrium model it focuses solely on the agricultural sector, taking other sectors as exogenous. MAgPIE solves on a spatially explicit resolution of up to 0.5° and is able to cluster grid cells in order to decrease computing time (Dietrich, 2011). It is coupled to the vegetation-hydrology model LPJmL (Bondeau et al., 2007), which delivers biophysical inputs on grid level (e.g. rainfed and irrigated yields, water requirements and constraints, and soil and vegetation carbon). The demand side is determined by an exogenous regression based on population, GDP, and time. Food supply is derived from linear step-wise production functions aggregated over spatial grids and land supply is represented by grid-specific land markets with endogenous land conversion based on expansion costs (Section 4.2). Yields per grid cell can be increased through investments in technological change, which are determined by a cross-region regression analysis between agricultural technological change investments (R&D and infrastructure) and agricultural land use intensity (Section 2.2). The model solves for net agricultural trade, which is based on a mixture of fixed self-sufficiency ratios and comparative advantage criteria (Section 3.2.3). More details on MAgPIE are presented in Section 3.2.1, 4.2.1 and 5.2.1 and the mathematical documentation in Appendix 1.

MAgPIE is programmed in GAMS (General Algebraic Modeling System), a programming language designed for solving optimization problems (Brook et al., 1988). The processing of input and output data of MAgPIE is mostly done with the programming language R (Ihaka and Gentleman, 1996).

1.4 Research objectives and thesis overview

The main objective of this research is to gain a better understanding of the agricultural system and its linkages to other sectors. Therefore, knowledge about how specific processes cause certain results is crucial and will lead to an improved and more comprehensive interpretation of results. The use of modelling techniques has the prior aim to highlight complex interrelations and to support the understanding of underlying processes. The better understanding will ideally lead to improvements in simulating future developments.

MAgPIE has the main goal of fulfilling future demand requirements under certain production constraints. In the coming decades global demand will further rise, which makes it necessary to increase production to a certain degree. In order to increase food production cropland has to be expanded (extensification), agricultural productivity has to be improved (intensification), or agricultural production has to be allocated in a more efficient way (specialisation). In the present thesis I will foremost focus on processes dealing with these potential options for higher food production in the future:

1. Extensification

   → expansion of cropland

2. Intensification:

   → intensification through irrigation agriculture (technical efficiency)
   → yield improvement through investments in technological change

3. Specialisation

   → increased liberalisation of international trade

Extensification in MAgPIE is modelled via endogenous cropland expansion. The main sources of expansion are intact and frontier forests and natural vegetation. Land use intensification is distinguished into technical efficiency and technological change (Fulginiti et al., 2004). In the first case, the yield gap between actual yields and the potential yield, caused by insufficient management and conditions, is reduced. Examples for this gap are insufficient utilisation of inputs like water, nutrients or weed control and poor management decisions. Through a better and more efficient combination of inputs actual yields can catch up on potential yields. In the second case, potential yields are increased due to technological change. If technological progress is fully adopted by farmers, actual yields will increase to the same extent and the relation between actual and potential yield stays constant. Typical examples for technological change are advancements in science which are successfully transmitted to practise, e.g. new breeding or improved irrigation techniques.

Finally, we consider specialisation as a way to use existing natural resources, foremost land, and water, in a more efficient way. International trade allows regions to specialize production according to comparative advantages and under the right framework conditions the same production level can be achieved with lower resource use. Although, current liberalisation efforts are stagnating on an international level, bilateral trade agreements and reduced transaction costs have contributed to an increased movement of agricultural goods in the past.

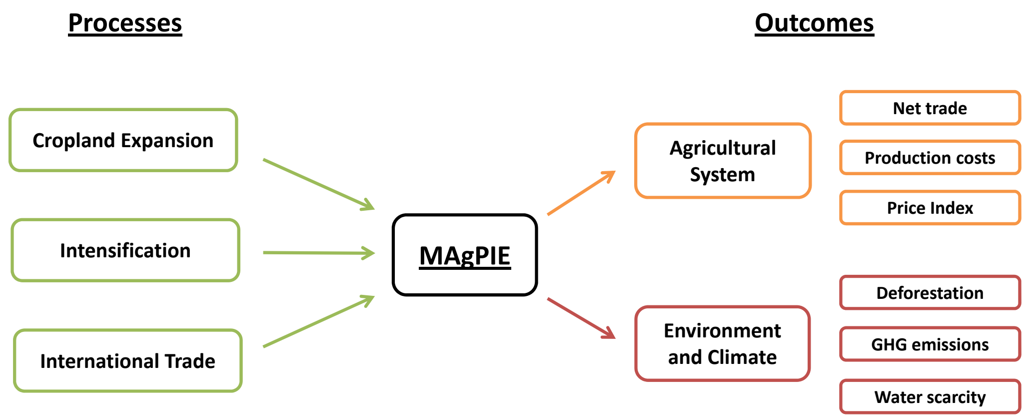


Figure 1.4: Main processes and outcomes of MAgPIE covered in the thesis

All three options to increase production do not come without external costs. In MAgPIE, it is possible to quantify related environmental feedbacks. Figure 1.4 illustrates processes and main outcomes considered in the thesis. Each of the three processes has significant influences on the agricultural system with consequences for net trade, production costs, and food prices. At the same time, impacts on the environmental and climate system, like greenhouse gas (GHG) emissions, water scarcity and deforestation rates, are highly uncertain. From this follows the overarching and guiding research question of this thesis:

How do intensification, cropland expansion and trade interact within the agricultural system and what are resulting environmental externalities with regards to land, water and emissions?

In order to be able to approach this question, it is broken down into specific research questions along the different papers. The first paper (Chapter 2) considers three questions:

– How can technological change (TC) in agriculture be reflected endogenously in a global land use model?
– How do production costs develop in relation to the land use intensity level?
– How do endogenous TC rates and endogenous land expansion rates interact in the future?

To answer these questions, we relate investments in technological change to the corresponding yield growth level in the future. As basis for the management level we take a land use intensity measure, called τ-factor (Dietrich et al., 2012). Secondly, we estimate the development of production costs with regards to land use intensity. Resulting functional relationships are implemented in MAgPIE and validated with historic and recent observations of FAO. The interplay with land expansion is illustrated with two scenarios on forest conservation.

In the second paper (Chapter 3), trade liberalisation is implemented guided by the following research questions:

– How can trade liberalisation be reflected in a global land use model?
– How does trade liberalisation affect trade balances, production costs, and prices?
– What are the consequences of trade liberalisation for land use and GHG emissions?

The process of trade liberalisation is implemented via two trading pools, reflecting fixed trade via self-sufficiency rates and free trade via comparative advantages. With three different trade scenarios possible outcomes for agriculture and environment are examined.

Since trade liberalisation leads to a huge shift in cropland area, scenarios and policy implications are further examined in the third paper (Chapter 4). Two research questions shape this paper:

– What are appropriate policy measures to reduce deforestation from increased trade?
– What is the impact of these measures on land expansion and required TC rates?

Tropical rainforest has many socio-economic and environmental functions and its protection is widely discussed. I implement three types of protection: direct protection, market regulation, and indirect protection via investments in agriculture. The interactions and implications on the agricultural system are examined.

Finally, I extend the analysis to the question of water scarcity (Chapter 5). The fourth paper concentrates on two research questions:

– How can irrigation agriculture be reflected in the model?
– How is water scarcity affected by trade liberalisation and changes in demand?

I start by implementing the process of irrigation agriculture in MAgPIE. Irrigation efficiency changes dynamically depending on the income level. Furthermore, the model can decide to invest in expansion of irrigation area under additional costs. Through the linkage with LPJmL, I am able to compute water shadow prices indicating the scarcity of freshwater used for irrigation. Simulations of trade liberalisation and changing demand patterns deliver insights about extent and change of local water scarcity.

1.5 Statement of contribution

The cumulative dissertation is based on four scientific articles, which I have published or are currently under review. For all articles I am the lead author and my individual contribution is described below. Nonetheless, developing and applying a large and complex model like MAgPIE is a joint effort of many people. As part of the research group "The Price of Land" at PIK, I have contributed to and benefited from this cooperative effort in many ways.

1st Paper (Chapter 2)
Together with Jan Philipp Dietrich, I developed idea and methodology, collected the data, and prepared the literature overview. We jointly performed the analysis and wrote the paper. Our co-authors supported us during this process and finally, reviewed the paper before submission.

2nd Paper (Chapter 3)
Based on discussions with Hermann Lotze-Campen, Alexander Popp and Anne Biewald, the idea for this paper emerged. I developed the methodology and implemented it in the model. Jan Philipp Dietrich, Benjamin Bodirsky, and Isabelle Weindl provided helpful advice during this process. I reviewed the literature, performed model simulations, and wrote the paper, which was finally commented by my co-authors.

3rd Paper (Chapter 4)
This paper came up as a follow-up study, since in the paper of Chapter 3 the policy dimension was missing. Therefore, I implemented scenarios covering possible forest protection measures and performed the analysis around it. The scenarios are based on an extensive literature review. Michael Krause gave helpful comments during this process. Finally, I wrote the paper, which was commented by my co-authors.

4th Paper (Chapter 5)
Together with Hermann Lotze-Campen and Dieter Gerten, I developed the idea of presenting the water shadow price in the context of trade liberalisation and diet change. I developed the input validation method and implemented water-related features in MAgPIE (dynamic irrigation efficiency and irrigation area expansion). I performed model simulations, the sensitivity analysis and wrote the paper. My co-authors supported me with helpful comments on the final version of the paper.

2 Forecasting technological change in agriculture - An endogenous implementation in a global land use model[1]

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Abstract

Technological change in agriculture plays a decisive role for meeting future demands for agricultural goods. However, up to now, agricultural sector models and models on land use change have used technological change as an exogenous input due to various information and data deficiencies. This paper provides a first attempt towards an endogenous implementation based on a measure of agricultural land use intensity. We relate this measure to empirical data on investments in technological change. Our estimated yield elasticity with respect to research investments is 0.29 and production costs per area increase linearly with an increasing yield level. Implemented in the global land use model MAgPIE ("Model of Agricultural Production and its Impact on the Environment") this approach provides estimates of future yield growth. Highest future yield increases are required in Sub-Saharan Africa, the Middle East and South Asia. Our validation with FAO data for the period 1995-2005 indicates that the model behavior is in line with observations. By comparing two scenarios on forest conservation we show that protecting sensitive forest areas in the future is possible but requires substantial investments into technological change.

[1]Reprinted version from Dietrich, J.P., C. Schmitz, H. Lotze-Campen, A. Popp, and C. Müller (2012), Forecasting technological change in agriculture - An endogenous implementation in a global land use model, *under review for Technological Forecasting and Social Change.*

2.1 Introduction

More than 200 years ago Thomas Malthus published his rather pessimistic population essay, in which he stated that population growth would be restricted by a slow growth rate in food production (Malthus, 1798). Now the world is inhabited by almost seven billion people, which marks an increase by about 600% since Malthus' times. One of the main shortcomings of his essay was the underestimation of technological change (TC) in agriculture (Trewavas, 2002).

However, during Malthus' times technological change was negligible and higher food production was almost exclusively due to an increase in production factors (Federico, 2005). Important innovations in agriculture from the 19th century onwards changed this pathway (Runge et al., 2003). Since then land-saving technological change has been the main driver for growth in agricultural output (Wik et al., 2008; Rosenzweig et al., 1988). Figure 2.1 shows the strong correlation between agricultural output and population during the last 200 years. Agricultural output has increased considerably, paving the way for strong population growth. Most of such increases in agricultural output have been the result of technological change induced by investments in Research & Development (R&D). One example is the so called "Green Revolution" in Asia and Latin America, initiated by international agricultural research institutes (Evenson and Gollin, 2003)[2].

While the importance of TC in agriculture is widely acknowledged in the recent literature (Alston et al., 2009; Alene and Coulibaly, 2009; Huffman and Evenson, 2006; Thirtle et al., 2003), in agricultural sector models or models of land use change, TC is implemented as an exogenous driver (Schneider et al., 2011; Wirsenius et al., 2010; Verburg et al., 2009; Wise et al., 2009; Heistermann et al., 2006). In these models, projections primarily depend on a fixed technology path rather than on internal model dynamics. This may lead to serious biases in model results due to an underestimation of the adaptability in the agricultural sector, especially in the longer run.

In this paper we present a first attempt of implementing endogenous technological change in a land use model, which means that the model can freely decide about the optimal rate of technological change in the future. For this purpose, we relate investments in technological change and corresponding yield growth to agricultural land use intensities. As a second step, we estimate empirically how the level of agricultural production costs per area evolves with the yield level. The methods are implemented in the global land use optimisation model MAgPIE ("Model of Agricultural Production and its Impact on the Environment") (Lotze-Campen et al., 2008, 2010; Popp et al., 2010) and the resulting technological change rates are validated with independent data. Finally, in order to illustrate the importance of the dynamic behaviour of TC, we compare two extreme scenarios on forest conservation which reflect the trade-off between agricultural land expansion and technological change.

[2]During the 1960s and 70s the International Maize and Wheat Improvement Center (CIMMYT) and the International Rice Research Institute (IRRI) developed high-yielding wheat and rice seeds.

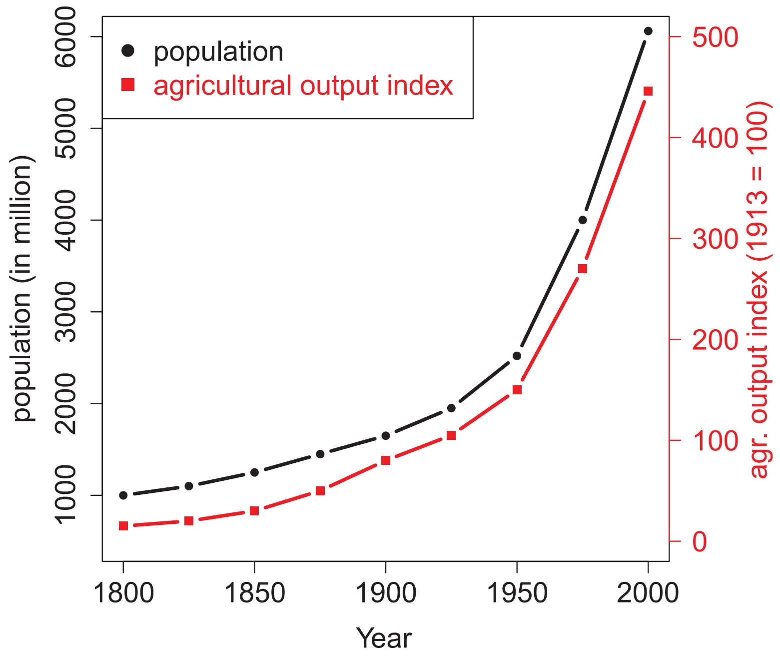

Figure 2.1: Historic development of agricultural production and population [own illustration based on Federico (2005) and United Nations (2005)]

2.2 Methodological framework

The endogenous implementation of agricultural TC is based on production costs and the effectiveness of R&D investments on yield changes (investment-yield ratio, IY) (see Table 2.1 for definitions). The IY ratio, describing TC investments required per unit of yield growth, evolves with the agricultural land use intensity. Accordingly, production costs (i.e. for use of inputs) are based on yield levels. For the purpose of measuring agricultural land use intensity we use the τ-factor developed by Dietrich et al. (2012). The τ factor is an output-related measure of land use intensity and captures the full spectrum of yield increasing technology and management options.

2.2.1 Investment-Yield ratio

Based on the τ factor it is possible to link investment costs for generating technological change directly to the level of land use intensity. We differentiate between two types of investment costs which influence the rate of technological change: first, public and private investments in agricultural R&D, and second, investments in infrastructure (e.g. transport and telecommunication). Data for public and private R&D investments is taken from IFPRI for the year 1981 (Pardey et al., 2006) and data for infrastructure investments is from the GTAP database, version 7 (Narayanan and Walmsley, 2008)

concept	**description**
agricultural land use intensity	degree of yield amplification caused by human activities (Dietrich et al., 2012)
τ-factor	measure proportional to agricultural land use intensity (Dietrich et al., 2012)
technological change (TC)	more efficient usage of the input factors land, labour or capital (Romer, 1990)
TC investments	composite of annual investments in R&D and infrastructure (e.g. transport and telecommunication) [US$/year]
investment-yield ratio (IY ratio)	TC investments required per human-induced unit yield growth and area [US$/ha]

Table 2.1: Concepts and terms used in this paper

(discounted from 2004 to 1995)[3]. Unfortunately, the GTAP database does not distinguish between one-time investments in infrastructure and maintenance costs. To get an estimate for annual investments in infrastructure the total GTAP infrastructure costs are corrected with a factor of 0.65, which is the average fraction of one-time investments on total infrastructure costs based on OECD (2010). The remaining 35% of the total infrastructure costs are maintenance costs and are treated as additional production costs.

Both investment costs, R&D investments and infrastructure investments, are divided by the average yield growth rate observed in the years 1990-1999 taken from FAO (FAOSTAT, 2010) to achieve investment costs per unit of yield growth. The reason for taking the R&D investment data of the year 1981 is the typical time lag between investment in R&D and its impact. The literature offers quite a wide range of various delays and lag-structures proposed for agriculture, ranging from a few years to several decades (Pardey and Craig, 1989; Alston et al., 1998; Fan et al., 2002; Cox et al., 1997). The chosen delay of 15 years matches the average delay used in literature and, according to Alston et al. (1995, 2000), the time which is needed to reach the maximum value of gross annual benefits.

The absolute amount of investment still depends on the size of a region: the bigger the region, the higher the variation in physical conditions. As a consequence, more research is needed to produce the same average growth rate compared to a smaller region with less variation in biophysical crop conditions. Consequently, we normalised investment relative to the agricultural area of a region. Specific R&D investment per unit of yield growth are computed as the ratio of R&D expenditures per area and the yield growth 15 years later. The same concept is applied for infrastructure investment, except that no time delay is assumed. Both components add up to the investment-yield ratio IY describing the TC investment per area required per unit of yield growth.

[3]Infrastructure investments are composed of investments in transport, water and energy distribution, telecommunication and financial services, all related specifically to the agricultural sector according to GTAP 7.

The relationship between IY ratio and τ is described by the elasticity ϵ_τ^{IY}, i.e. the proportional relationship between an increase in τ and an increase in the IY ratio.

$$\frac{dIY(\tau)}{IY(\tau)} = \epsilon_\tau^{IY} \cdot \frac{d\tau}{\tau} \tag{2.1}$$

The elasticity ϵ_τ^{IY} is estimated via a regression analysis. Since agricultural R&D data is generally aggregated over all agricultural sectors and spillover effects are expected (van Meijl and van Tongeren, 1999; Evenson, 1989), we used an aggregated version of τ covering all crops for the regression.

2.2.2 Correlation with production costs

With improving agricultural technology and rising crop yields, production costs per hectare for fertilizer, machinery, and other input factors also rise. Since we endogenise the relationship between TC investment and land use intensity (Eq. 1), we also have to describe the relationship between yield levels and production costs. Data for production costs is taken from the GTAP 7 Data Base (Narayanan and Walmsley, 2008) and yield data is taken from FAOSTAT (2010). The data for small producing countries is expected to be insufficiently accurate (Horridge and Laborde, 2008). Therefore, only the top producing countries for each crop are taken into account, representing at least 90% of total crop production and at minimum 1/3 of all available countries (31 countries) in the analysis (an exception is oil palm, which is only produced in 20 countries worldwide).

A standard linear regression analysis of this data shows that the residuals are not normally distributed and would give biased results. Therefore, we have applied a correlation analysis between (a) yield and costs per area and (b) yield and costs per ton using the Pearson correlation coefficient (Rodgers and Nicewander, 1988) as well as the Kendall rank correlation coefficient (Kendall, 1938). We use two different correlation coefficients, in order to reveal potential measure-related biases in the analysis. Whereas the Pearson correlation coefficient measures the magnitude of the linear dependence between two variables, the Kendall rank correlation coefficient measures just any correlation based on a rank test (Kendall and Gibbons, 1990). Since residuals in our data set are non-normally distributed, the significance of the Pearson test may be biased, if samples sizes are too small (Kowalski, 1972).

2.2.3 Model implementation

The global land use model MAgPIE ("Model of Agricultural Production and its Impact on the Environment") has been developed to generate future land use and agricultural production patterns, addressing a wide range of scenarios on population and income growth throughout the 21st century. It is a recursive dynamic model working on a regular spatial grid with a cell size of about $0.5° \times 0.5°$ (approximately $50 \times 50km^2$ at the equator). The model works on ten-year time steps. On the biophysical side, it uses spatially explicit data on potential crop yields, land and water availability taken from the dynamic global vegetation model LPJmL (Bondeau et al., 2007). Economic data is used at the aggregate level of 10 economic world regions [4]. For future demand trajectories the model derives specific land use patterns and costs of agricultural production for each grid cell. These patterns are initially based for the year 1995 on external data for population (CIESIN et al., 2000) and gross domestic product (GDP) (World Bank, 2001). Future projections are internally derived based on future scenarios defined in the ADAM project [5] and eplained in van Vuuren et al. (2009). The food energy demand for the year 1995 is taken from FAOSTAT (2008). The share of traded goods is kept constant over time and is based on self-sufficiency ratios for the year 1995 (FAOSTAT, 2008). More information on model structure and features can be found in detail in Lotze-Campen et al. (2008, 2010); Popp et al. (2010, 2011b). A mathematical description of the model is presented in Appendix 1.

Figure 2.2 shows a schematic overview of the endogenous implementation of technological change in MAgPIE. Investment in TC leads to yield increases, which cause the τ-factor to rise. This implies an increase in production costs per area as well as a rise in the IY ratio. In order to achieve one unit of yield increase in a certain time step, a larger amount of TC investment has to be mobilised than in the previous period. In Appendix 2 we explain some further implementation issues dealing with the recursive dynamic structure of MAgPIE.

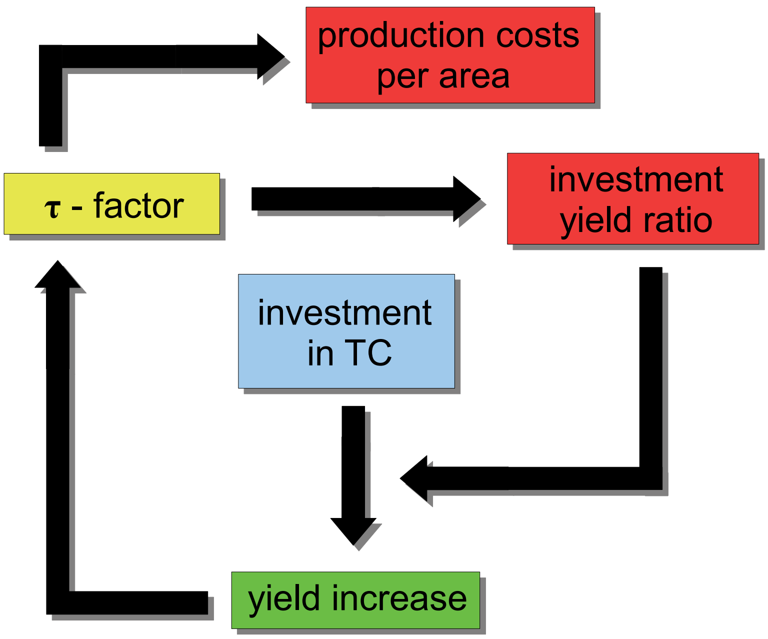

Figure 2.2: Implementation of technological change in MAgPIE (schematic)

[4] AFR = Sub-Sahara Africa, CPA = Centrally Planned Asia (incl. China), EUR = Europe (incl. Turkey), FSU = Former Soviet Union, LAM = Latin America, MEA = Middle East and North Africa, NAM = North America, PAO = Pacific OECD (Australia, Japan and New Zealand), PAS = Pacific Asia, SAS = South Asia (incl. India)

[5] Adaptation and Mitigation Project, URL: http://www.adamproject.eu/

2.2.4 Validation and scenarios

For the validation we compare long-term trends of simulated τ development from 1995 to 2060 with observed data from 1960 to 2005, with a special focus on the overlap in 1995-2005. We use historical data from FAO on yield growth, which was neither part of the model parameterization nor calibration. Based on this data the changes in τ are calculated backwards starting from 2005.

In order to show the interplay between rates of deforestation and endogenous technological change in agriculture we have compared two scenarios: one scenario which is assuming full conservation of all intact and frontier forests (IFF) and a second scenario without any IFF conservation. IFF is defined as undisturbed natural forest (i.e. the Amazonian rainforest) which includes intact forest landscapes and frontier forests (Krause et al., 2009). IFF conservation in MAgPIE is modeled by excluding the IFF areas from the land area available for agricultural land expansion. Expansion involves additional costs for intraregional transport and physical conversion. Intraregional transport costs reflect the distance to the next market and account for the accessibility and quality of the infrastructure. The costs are based on GTAP transport costs (Narayanan and Walmsley, 2008) and a 30 arc-second resolution data set on travel time (Nelson, 2008). The second cost type, land conversion costs, involves the preparation of the land and basic infrastructure and is based on country-level marginal access costs (Sohngen et al., 2009).

We have chosen these two extreme scenarios to represent the full spectrum of possible policy decisions. On the one hand, forest protection is a clearly stated objective of many governments and international organisations (Miles and Kapos, 2008) but on the other hand, deforestation of IFF is happening all over the world (Forner et al., 2006) and efficient protection mechanism are still lacking (Gumpenberger et al., 2010). The scenarios help to make the full trade-off between agricultural land expansion and technological change transparent. Besides the differences in handling of the IFF areas, both scenarios apply the same conditions as explained in section 2.2.3.

2.3 Results

2.3.1 Regression and correlation

The regression analysis between IY ratio and the τ-factor results in the relationship shown in equation 2.2. Figure 2.3 shows the relationship in a graph for the 10 world regions of the MAgPIE model.

$$IY(\tau_i) = (1.9 \pm 0.4) \cdot 10^3 \cdot \tau_i^{2.4 \pm 0.9} \tag{2.2}$$

P-values of the t-tests for prefactor a and exponent/elasticity ϵ are $p_a = 0.002$ (**) and $p_\epsilon = 0.04$ (*). The elasticity between IY ratio and the τ-factor ϵ_τ^{IY} has a value of 2.4 with a standard error of 0.9. As previously explained, changes in τ are proportional to changes in yield, and therefore we can transform this elasticity into an elasticity

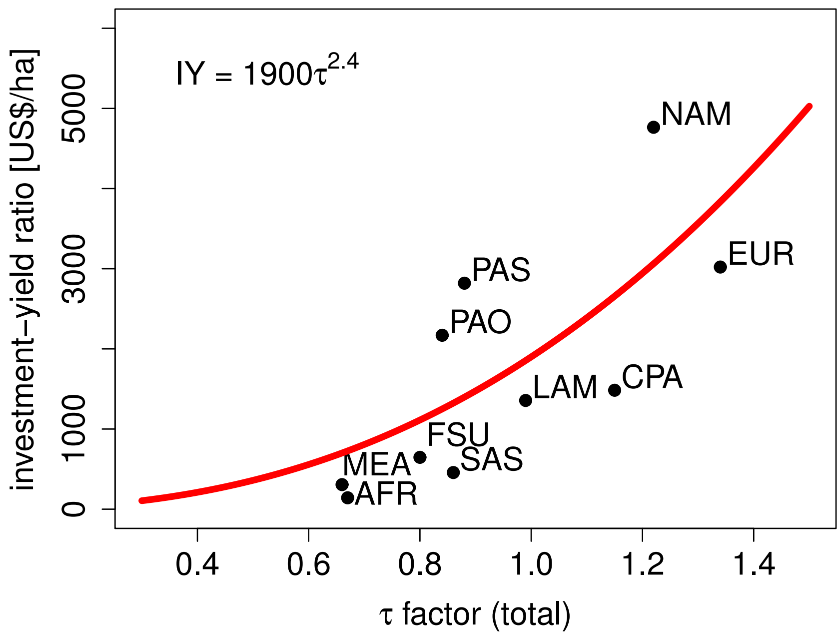

Figure 2.3: investment-yield ratio in relation to τ-factor

of yield with respect to accumulated TC investments (I), which is a more common representation (Equation 2.3). The result is close to the value of $\epsilon_I^{yld} = 0.296$, as reported by (Nelson et al., 2009).

$$\epsilon_I^{yld} = \frac{1}{\epsilon_\tau^{IY} + 1} = 0.29 \pm 0.08 \tag{2.3}$$

With regard to the relationship between production costs and yield level, Table 2.2 shows the Pearson correlation coefficients and the Kendall rank correlation coefficients. All correlations are positive and in most cases at least significant at the 95% level. In the Kendall rank correlation test all crops except tropical cereals, oil palm and sugar cane show significant correlations at the 99.9% significance level. In the Pearson correlation tests the results are less significant, but still 10 out of 16 crops show significant correlations at the 95% level. Table 2.3 shows the same information for the relationship between yields and production costs per ton. However, almost none of the tested crop types shows a significant correlation. Comparing the results in both tables suggests the existence of a positive correlation between yields and area-related production costs, but no correlation between yields and output-related production costs. Based on this result production costs per ton have been implemented as a constant input for the model, which leads to a linear increase of production costs per area with yield.

crop types		Pearson			Kendall		
		correlation		p-value	correlation		p-value
cereals	temperate	0.81	***	0.000	0.63	***	0.000
	tropical	0.49	*	0.019	0.23		0.140
	maize	0.70	***	0.000	0.61	***	0.000
	rice	0.42	*	0.019	0.57	***	0.000
oilcrops	groundnut	0.17		0.410	0.47	***	0.001
	oil palm	0.07		0.803	0.23		0.228
	rapeseed	0.56	**	0.002	0.55	***	0.000
	soybean	0.08		0.689	0.47	***	0.000
	sunflower	0.68	***	0.000	0.45	***	0.000
sugar	beet	0.65	**	0.002	0.53	***	0.001
	cane	0.37		0.107	0.14		0.422
others	cassava	0.35		0.084	0.47	***	0.001
	potato	0.37	*	0.046	0.58	***	0.000
	pulses	0.75	***	0.000	0.52	***	0.000
	cotton	0.26		0.171	0.49	***	0.000
	others	0.62	***	0.000	0.43	***	0.001

Table 2.2: Correlation between yield and production costs per area
(* p≥95%, ** p≥99%, *** p≥99.9%)

crop types		Pearson			Kendall		
		correlation		p-value	correlation		p-value
cereals	temperate	-0.06		0.771	0.15		0.250
	tropical	0.02		0.941	-0.07		0.676
	maize	0.27		0.151	0.25		0.058
	rice	0.28		0.126	0.29	*	0.022
oilcrops	groundnut	-0.10		0.628	0.23		0.118
	oil palm	-0.03		0.912	0.15		0.450
	rapeseed	0.29		0.136	0.26		0.055
	soybean	-0.06		0.753	0.25		0.066
	sunflower	0.12		0.531	0.22		0.103
sugar	beet	0.42		0.068	0.30		0.074
	cane	-0.22		0.352	-0.13		0.461
others	cassava	0.32		0.118	0.25		0.088
	potato	0.22		0.246	0.33	**	0.010
	pulses	0.43	*	0.040	0.38	**	0.010
	cotton	0.00		1.000	0.28	*	0.029
	others	0.42	*	0.025	0.24		0.072

Table 2.3: Correlation between yield and production costs per ton
(* p≥95%, ** p≥99%, *** p≥99.9%)

crop types		costs [US$/t]	countries	prod. share
cereals	temperate	130	31	0.95
	tropical	70	31	0.97
	maize	90	31	0.96
	rice	110	31	0.99
oilcrops	groundnut	180	31	1.00
	oil palm	30	20	1.00
	rapeseed	210	31	0.99
	soybean	150	31	1.00
	sunflower	130	31	0.99
sugar	beet	220	31	0.98
	cane	50	31	0.99
others	cassava	350	31	0.99
	potato	1230	31	0.91
	pulses	160	31	0.94
	cotton	620	31	0.99
	others	1130	31	0.92

Table 2.4: Crop-specific, average costs per ton, number of countries used for averaging and the total production share of these countries

Table 2.4 shows the calculated costs per ton together with the number of countries included in this calculation and the share of total production covered by these countries. These costs per ton are used in MAgPIE for the calculation of production costs (see Appendix 1).

2.3.2 Simulation results

Figure 2.4 shows the projected τ development (2005-2060) for maize compared to past observations of the FAO (1960-2005) in the forest conservation scenario. Maize is chosen as an example since this is one of the most important crops and is grown in all parts of the world. Regions like Sub-Saharan Africa (AFR) and North America (NAM) show very strong increases in τ. However, the strongest increase is projected for the Middle East and North Africa region (MEA). This enormous increase is in line with FAO data for this region for the period since the 1980s. Overall three groups can be distinguished: Regions with increasing growth rates (MEA, AFR), constant rates (NAM, LAM, SAS and PAS) and decreasing rates (CPA, EUR, FSU, PAO). PAO is a special case with small growth rates in the past but vanishing growth rates in the projections until 2040.

Figure 2.5 shows the model results of both scenarios (full forest conservation and no forest conservation) compared with FAO observations in greater detail for the aggregate of all crops. It is important to note that the FAO data used for validation was not taken as model input, neither as direct source, nor for calibration purposes. For a direct comparison between observations and model results, we focus on the overlap from 1995

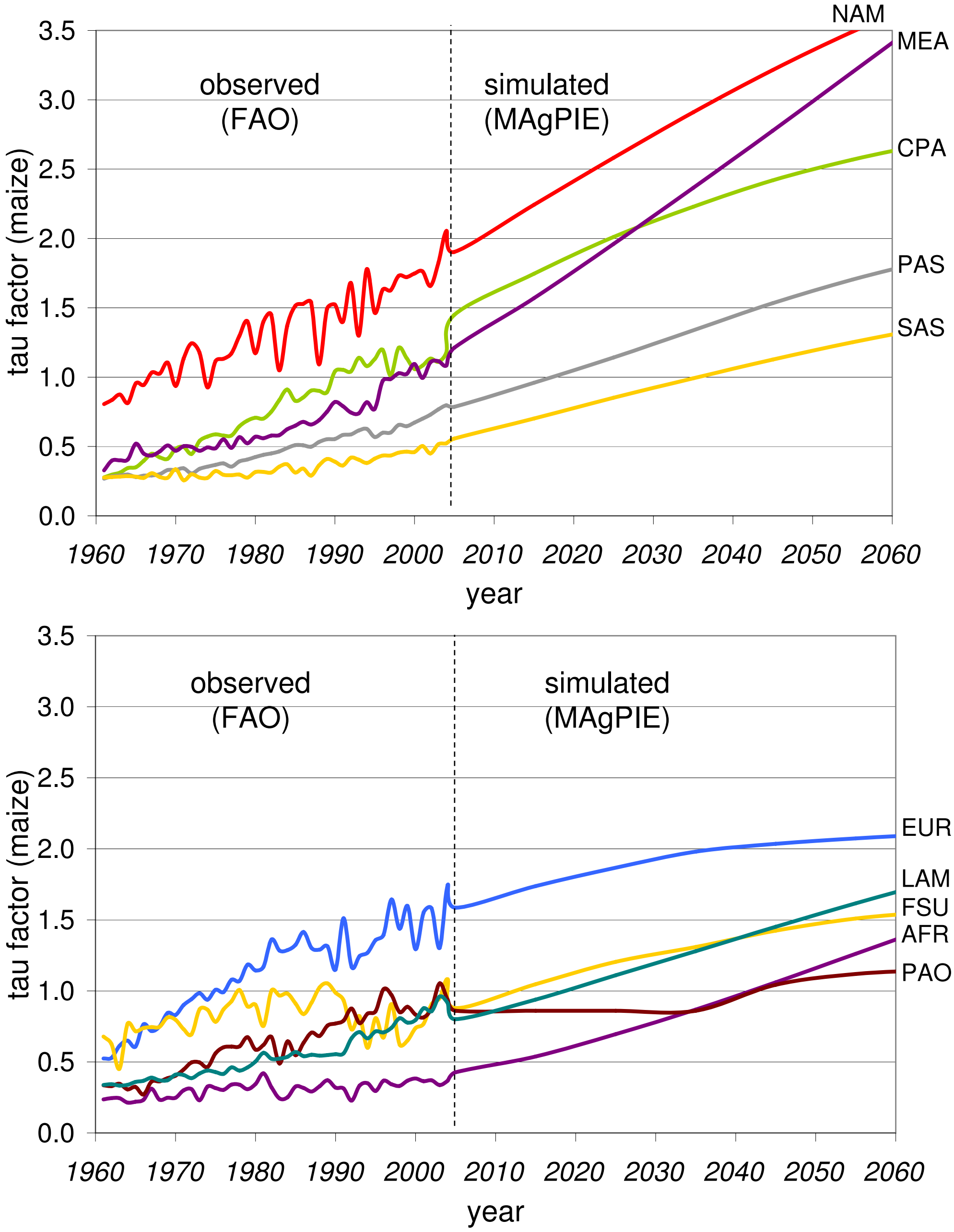

Figure 2.4: Observed and simulated τ-factor for maize in the ten world regions under a forest protection scenario

to 2005. Moreover, the model results can be validated against the general trend in the observed data.

For some regions the scenario projections deliver quite similar or even identical results while the projections for other regions strongly depend on the chosen scenario. Especially, the three regions with huge rainforest areas (LAM, AFR, and PAS) show large differences in projections. Looking at these three regions also the agreement between observation and validation is quite diverse: In AFR historic growth rates are significantly lower compared to the rates of both projections. However, at the 10 year overlap (1995-2005) the differences are smaller, especially in the scenario without forest conservation. In contrast, LAM shows the exact opposite behavior. In the scenario without forest conservation, growth rates are underestimated, while in the forest conservation scenario projections are in good agreement with historic trends, although the model still seems to underestimate the observed growth rates in the overlapping period. In PAS, historic trends fit quite well to the forest conservation projection, whereas in the overlapping period observational data shows some stagnation. The projection without forest conservation illustrates the same effect, even though in a more extreme manner (20 years stagnation instead of only 5 years).

In the remaining regions the differences between both scenarios are small. For EUR, MEA, and NAM the general trend as well as the overlap show a good agreement between observation and simulation. In CPA the trend fits well, but in the observed data from 1995 on appears a stagnation (similar to the situation in PAS) which is not reproduced by the simulations. The results for FSU are hard to judge, because the historic data is strongly affected by fluctuations due to the political transformation after 1990. PAO shows weak growth rates in the historic trend, but none in the simulations until 2040 and none in the observed data between 1995-2005. For SAS it seems that both projections slightly overestimate the real trend, even though the differences are only marginal. Overall, we can state that none of the regions shows huge discrepancies between observation and simulation, but for some regions the forest-conservation scenario shows a better agreement (LAM, PAS) while other regions agree more with the no-forest-conservation scenario (AFR, CPA, SAS).

Differences in TC rates between scenarios also directly affect land use patterns. Figure 2.6 and 2.7 show the share of cropland in total land area in 2065 for the forest conservation scenario (Figure 2.6) and the scenario without forest conservation (Figure 2.7). The largest differences are obtained in the regions LAM, AFR and PAS, which are also most sensitive in the τ-factor comparison. In these three regions Brazil, the Democratic Republic of the Congo and Indonesia are most strongly affected from deforestation. Smaller changes are simulated in Canada, Russia, Mexico and Australia. Due to the absence of relevant IFF areas in the rest of the world, no other significant changes do occur.

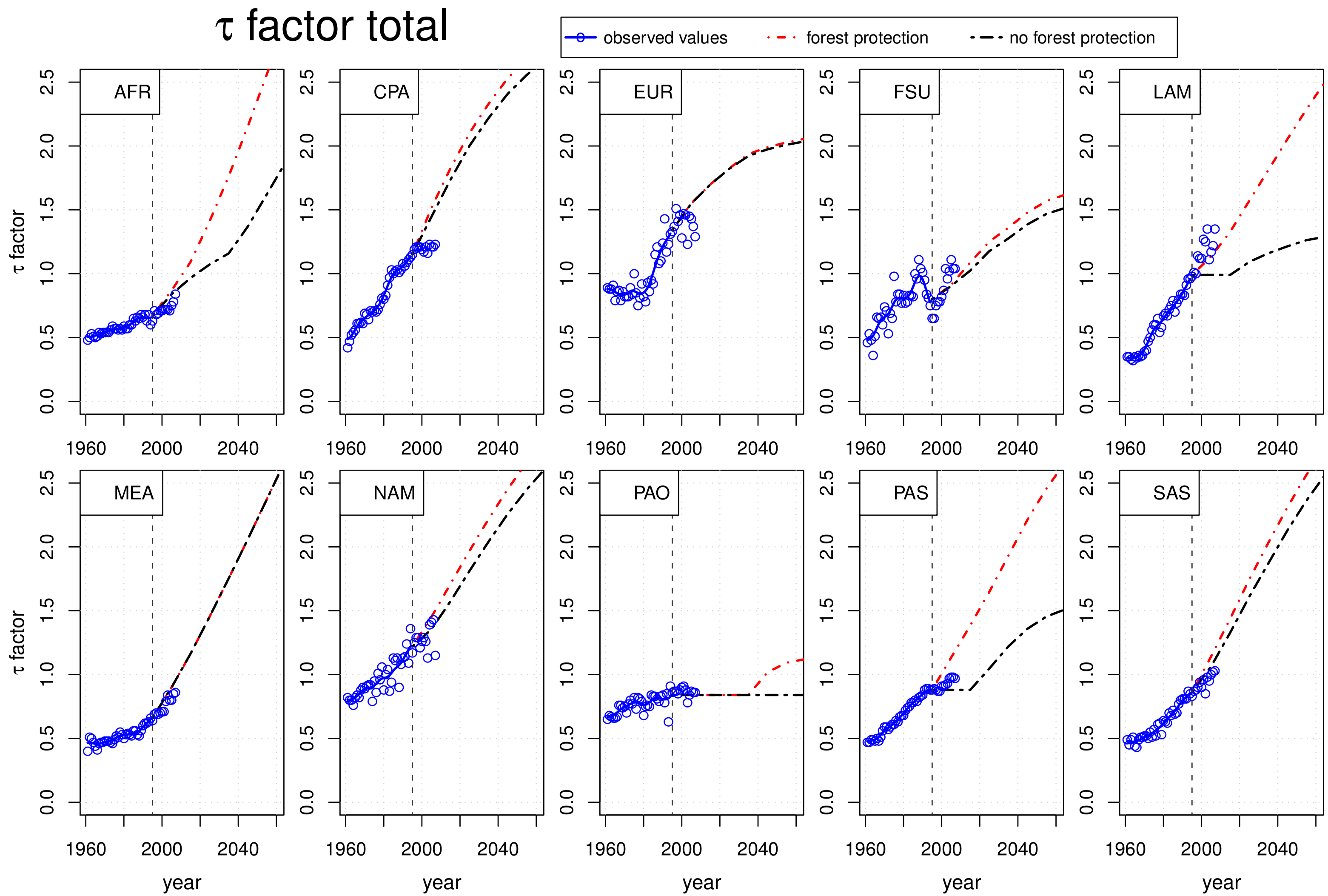

Figure 2.5: Comparison of MAgPIE model projections 1995-2060 in a forest protection scenario (red dotted line) and a scenario without forest protection (black dotted line) with FAO observations 1960-2005 (blue dots) and its running mean (blue line)

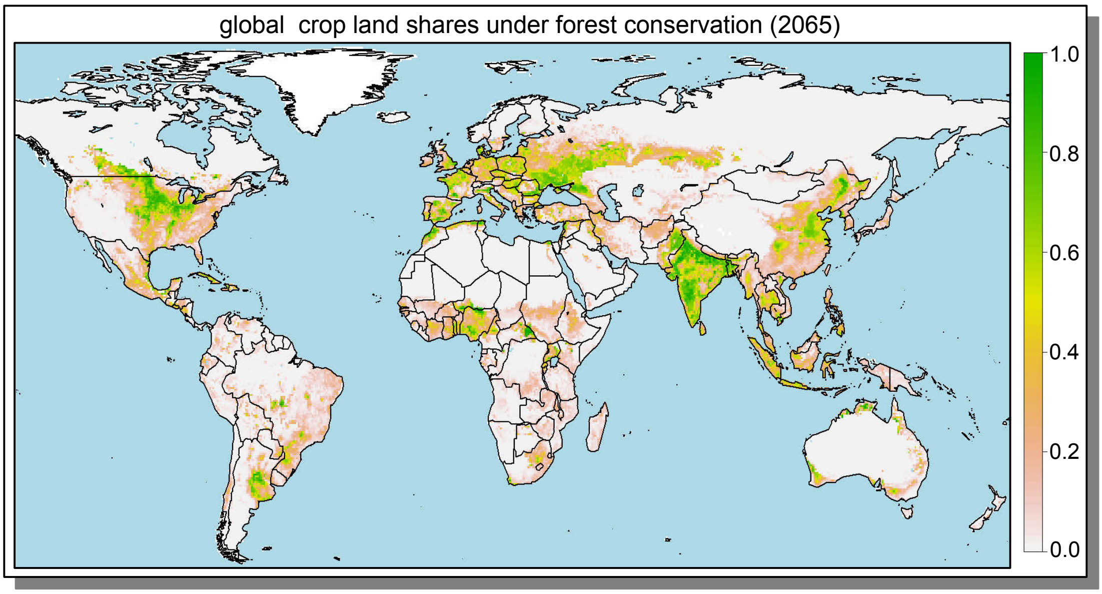

Figure 2.6: Global total cropland shares in a intact and frontier forest protection scenario in 2065

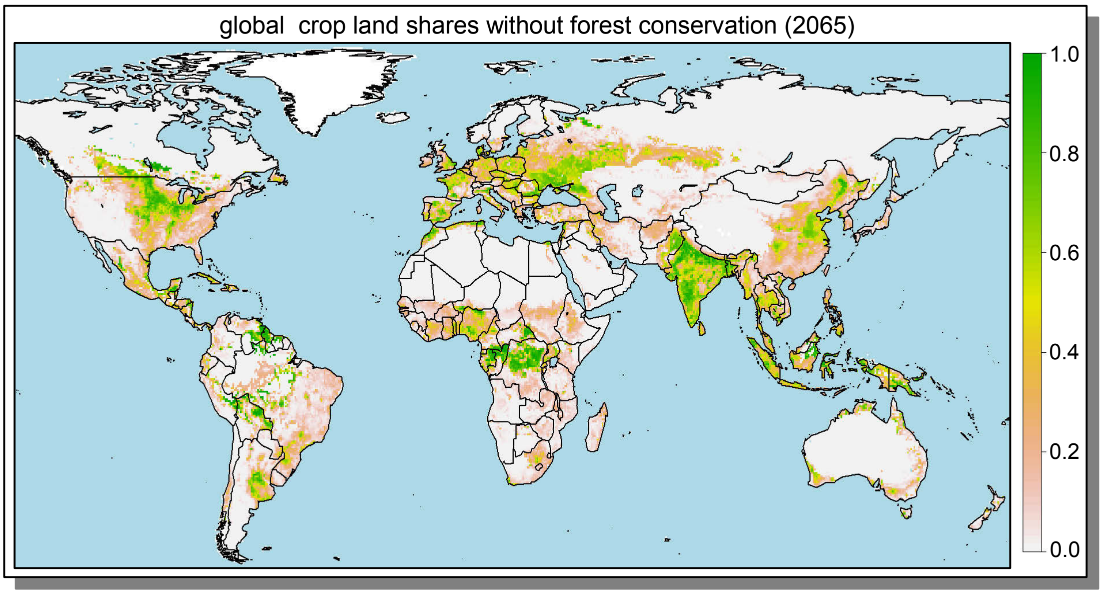

Figure 2.7: Global total cropland shares in absence of any intact and frontier forest protection in 2065

2.4 Discussion

Technological change is the crucial driver for increasing agricultural yields. However, in land use models technological change is usually implemented in an exogenous way leading to static pathways without any dynamic interaction (i.e. (Wise et al., 2009; Heistermann et al., 2006)). The main reason for using an exogenous path is that although the relationship between R&D investments in agriculture and technological change is well documented (Alston et al., 2009; Alene and Coulibaly, 2009; Thirtle et al., 2003; Alston et al., 2000; Pardey and Craig, 1989), the exact influence of R&D on technological change is still unknown. Several reasons exist for this knowledge gap. First, available time series of R&D investments are still relatively short (less than 30 years) and often incomplete (Pardey and Beintema, 2001). Second, as Evenson (1989) showed, spillover effects are of major importance in agricultural research and hamper the correct assignment of R&D investments to their impact. Third, success in R&D is hard to predict. High investment may fade away without producing any output, whereas in other instances low investment may create considerable results. Finally, no clear boundary exists between R&D investments in different sectors. In many cases inventions in one sector are based on inventions in other sectors. In a partial analysis of a specific R&D sector, e.g. agricultural R&D, these cross-connections cannot be considered.

We presented a new method which addresses most of these information deficiencies. The problems of high uncertainty and unpredictable rates of return associated with investments and the problem of spillovers are partially compensated for by using a high aggregation level of only ten world regions. On the other hand, this means that our approximation is only valid at coarse scales and becomes invalid when applied to finer scales. In addition, we address the problem of missing time series data by using the land use intensity indicator as proxy and assuming the same development path for all world regions. Our approach estimates the level and evolution of the investment-yield ratio relative to the τ factor, an output-related measure for agricultural land use intensity. The main advantage over other measures, like the yield gap analysis (Neumann et al., 2010), is that it includes technological change as a source of growth. A more detailed comparison to other concepts which analyse agricultural potentials is provided in Dietrich et al. (2012).

The regression analysis reveals that a higher level of agricultural land use intensity coincides with a higher IY ratio. Furthermore, the yield elasticity with respect to accumulated TC investments $\epsilon_I^{yld} = 0.29$ is in line with an expert assessment (Nelson et al., 2009). Results confirm that the yield level is correlated with production costs per area. Since marginal production costs are constant, every additional production unit faces the same amount of additional costs. Consequently, farmers will adopt the new technology since they expect higher yields at constant costs per ton.

Our τ projections for maize provide rich insights with regard to future yield trends. The strong increase in Africa indicates what kind of yield growth rates are required to meet the soaring demand under a forest conservation scenario. North America, as the leading region for maize production, continues with high yield growth rates. The Middle

East and North Africa region (MEA) require even higher growth rates. This region faces unfavorable cropping conditions and at the same time a higher demand increase. Under these conditions, huge investments in technological change are required. In contrast, Europe continues along its trend over the past two decades when maize yields have not improved much. The Asian regions, starting from a lower yield level and facing a higher demand pressure in the future, have higher growth rates compared to Europe. Lastly, Latin America follows its strong yield growth path since the early 1990s, with high investments in the agricultural sector.

The validation of simulated output with observed data supports our model implementation. Especially the long-term trend is reproduced well for most regions, while the observed data in the overlapping period 1995-2005 often shows some unexpected changes in dynamics, such as stagnation in some cases. A hint for an interpretation of these changes in dynamics can be found in the simulation results of the scenario without forest conservation: The projections for LAM as well as for PAS show also a temporary stagnation in growth rates similar to the observed stagnations in CPA and PAS. In the model, additional production is achieved exclusively by land expansion into IFF. However, in both regions the model switches again to yield increases due to technological change.

AFR is represented best by the scenario without forest conservation, LAM by the forest conservation scenario, and PAS by a mixture of both. This is in line with the political situation in these regions. While LAM is able to trigger investments in R&D on a level which is sufficient to remove the land expansion pressure based on agricultural demands (there are still other reasons for deforestation), AFR fails to do so. PAS seems to have a mixed situation with partial success. The results illustrate that, especially in AFR, R&D investments have to be increased tremendously to meet the demand without cutting down the rainforest in Central Africa. A reason for relatively weak validation results in a few regions is that demand and trade are rather inflexible in the current version of the MAgPIE model. In regions, like LAM or CPA, this might have strong impacts on future productivity levels. Notwithstanding, the overall validation results indicate the robustness of the approach, since the observed data is not considered as input for the analysis and are independent of the model results.

2.5 Conclusion

During the lifetime of Thomas Malthus and before, growth in agricultural output was almost exclusively a result of growth in the use of input factors. This changed by the end of the 19th century and since then agricultural output has been mainly driven by increases in productivity. However, agricultural sector and land use models do not cover technological change as an endogenous driver. In order to fill this gap, we have presented a model approach for an endogenous implementation of technological change.

Our statistical analysis indicates that the investment-yield ratio increases in a disproportionate way to land use intensity (measured by the τ-factor) and that production costs are linearly correlated with yield levels. Our simulation model results show that regions with high demand projections, like Sub-Saharan Africa, or with low potentials for land expansion, like Middle East and South Asia, have to make huge investments in future technological change. While the Middle East region and South Asia show this trend already in the observed data, Sub-Saharan Africa shows this trend only since 1995. Hence, to meet the projected challenges in economic development and growing agricultural demand, it seems indispensable for countries in Sub-Saharan Africa to increase investments in R&D and infrastructure in order to meet the demand. The scenario on forest conservation exemplifies that investments in agricultural R&D have to be increased considerable in order to be able to protect sensitive forest areas under otherwise unchanged conditions. Overall, the endogenous implementation of technological change improves the long-term projection quality of global agricultural models and is a further step towards more realistic future scenarios for agriculture.

3 Trading more food: Implications for land use, greenhouse gas emissions, and the food system[1]

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Abstract

The volume of agricultural trade increased by more than ten times throughout the past six decades and is likely to continue with high rates in the future. Thereby, it largely affects environment and climate. We analyse future trade scenarios covering the period of 2005-2045 by evaluating economic and environmental effects using the global land-use model MAgPIE ("Model of Agricultural Production and its Impact on the Environment"). This is the first trade study using spatially explicit mapping of land use patterns and greenhouse gas emissions. We focus on three scenarios: the reference scenario fixes current trade patterns, the policy scenario follows a historically derived liberalisation pathway, and the liberalisation scenario assumes a path, which ends with full trade liberalisation in 2045. Further trade liberalisation leads to lower global costs of food. Regions with comparative advantages like Latin America for cereals and oil crops and China for livestock products will export more. In contrast, regions like the Middle East, North Africa, and South Asia face the highest increases of imports. Deforestation, mainly in Latin America, leads to significant amounts of additional carbon emissions due to trade liberalisation. Non-CO_2 emissions will mostly shift to China due to comparative advantages in livestock production and rising livestock demand in the region. Overall, further trade liberalisation leads to higher economic benefits at the expense of environment and climate, if no other regulations are put in place.

[1]Reprinted with permission from Elsevier: Schmitz, C., A. Biewald, H. Lotze-Campen, A. Popp, J.P. Dietrich, B. Bodirsky, M. Krause, and I. Weindl (2012), Trading more food: Implications for land use, greenhouse gas emissions, and the food system, *Global Environmental Change* 22(1), 189-209.

3.1 Introduction

During the last decades, the trade volume of agricultural goods has increased in an unprecedented way. Whereas between 1950 and 1955 every year an agricultural value of around 80 billion US/$ was exported, it increased to an annual average of 827 billion US/$ in the period from 2005 to 2008 (FAOSTAT, 2010). Two developments are responsible for this trend. First, technological change reduced transport and transaction costs for trading, and second, agricultural trade was liberalised after the huge domestic support following the Second World War (Hummels, 2007; Josling et al., 2010; Anderson, 2010).

Evaluating the consequences of increased trade, most studies focus on economic indicators, like distributional effects, poverty impacts, and welfare (Anderson and Tyers, 1993; Martin and Winters, 1996; Corden, 1997; Bouët et al., 2005; Hertel et al., 2009). Only since the mid-1990s trade economists started to consider the relationship between agricultural trade and the environment in their analyses, often not differentiating between agricultural and non-agricultural trade (Tamiotti et al., 2009). Some early studies state a positive impact of more liberalised trade on the environment (Anderson, 1992; Antweiler et al., 2001) or draw a mixed picture (Cole, 2000; Baek et al., 2009). Copeland and Taylor (1994) show with a simple theoretical model how world trade liberalisation leads to less environmental pollution in the North but to an increased level in the South. Lopez (1994) concludes that trade increases resource degradation if producing countries are not including production externalities in product prices. More sophisticated econometric studies indicate a clear positive relationship between trade liberalisation and CO_2 emissions (Cole and Elliott, 2003; Managi, 2004; Frankel and Rose, 2005).

Whereas all these studies focus on the past, some more recent studies include environmental effects in trade models or coupled versions of biophysical and economic models to predict the future impact of trade liberalisation. Verburg et al. (2009) use the coupled LEITAP-IMAGE model to analyse the impacts of trade liberalisation on greenhouse gas (GHG) emissions. They conclude that overall GHG emissions increase by about 6% in 2015, when full trade liberalisation by 2015 is compared with the "no-new policy scenario" from OECD. Similar studies by van Meijl et al. (2006) and Eickhout et al. (2009) show that trade liberalisation leads only to small land-use shifts in Europe but dramatic shifts in Africa and other developing regions resulting in negative implications for the environment.

In contrast to these studies, our analysis combines the results of several environmental and economic indicators in order to get a more comprehensive picture. We use the spatially explicit economic land use model MAgPIE ("Model of Agricultural Production and its Impact on the Environment") (Lotze-Campen et al., 2008, 2010; Popp et al., 2010) to run different trade liberalisation scenarios. As an advantage to other models, MAgPIE takes biophysical information directly into account from the grid-based Lund-Potsdam-Jena dynamic global vegetation model with managed land (LPJmL) (Bondeau et al., 2007). In addition to the detailed representation of economic and environmental aspects, our modelling framework differs from comparable models by considering the interplay of land expansion and yield increasing technological change in an endogenous way (Schmitz et al., 2010).

In this study we investigate the implications of different trade liberalisation scenarios on global production costs, technological change rates, land use dynamics, deforestation rates, and greenhouse gas emissions over the coming four decades. To do so, we first explain the model framework (section 3.2.1), outline the method of trade simulation (section 3.2.3), illustrate the calculation of GHG emissions (section 3.2.4), as well as present the applied scenarios (section 3.2.5). Chapter 3.3 illustrates the results of the analysis. In chapter 3.4 and 3.5, we discuss the results and possible policy implications and draw the conclusions.

3.2 Model and scenarios

3.2.1 Model framework

The global land-use model MAgPIE is a recursive dynamic optimization model with a cost minimization objective function (Lotze-Campen et al., 2008, 2010; Popp et al., 2010). The biophysical supply side of the model is simulated spatially explicit using 0.5 degree data aggregated to 1000 clusters. The demand side is represented by ten world regions (see Appendix 2). The required calories in the demand categories are initially derived from population data (CIESIN et al., 2000) and income growth (Gross Domestic Product per capita) (World Bank, 2001) for the year 1995. These data are regressed on a cross-sectional basis with country data on food and non-food energy intake. Future demand is then based on a medium population projection and a medium economic growth scenario (however, with optimistic assumptions for China and India), both defined in the ADAM project[2] and explained in van Vuuren et al. (2009). The resulting demand calories are produced by 16 cropping (see Table 2 in Appendix 2). MAgPIE simulates time steps of 10 years (starting in 1995) and uses in each period the optimal land-use pattern from the previous period as a starting point.

The five livestock activities are related to specific feed energy requirements per animal product and per region. These requirements are met by a certain mixture of pasture, fodder, and food crops again depending on the region and animal type. The data are derived from Wirsenius (2000) and contain minimum requirements for maintenance, growth, lactation, reproduction and other basic biological needs. Moreover, we differentiate between a general allowance for basic activity and temperature effects as well as by using extra energy expenditures for grazing. For more details we refer to Weindl et al. (2010). These differences in the livestock systems cause different emission levels from livestock which are explained in more detail in section 3.2.4. From these data Africa has the lowest efficiency whereas Europe has the most efficient systems in 1995.

The biophysical inputs (e.g. yields) for MAgPIE are derived from the grid-based Lund-Potsdam-Jena dynamic global vegetation model with managed land (LPJmL)

[2]Adaptation and Mitigation Project, URL: http://www.adamproject.eu/

(Bondeau et al., 2007). LPJmL is a process-based model which considers soil, water, and climatic conditions, like CO_2, temperature and radiation in an endogenous way. The model runs are based on climate projections from HadCM3 (Hadley Centre Coupled Model, version 3) (Cox et al., 1999) and SRES A2 (Special Report on Emissions Scenarios) (Nakicenovic and Swart, 2000). The inclusion of the hydrological cycle and a global map of irrigated areas (Döll and Siebert, 2000) allow LPJmL to differentiate between rainfed and irrigated yields. Irrigated areas receive their additional water from the natural runoff and its downstream movement according to the river routing in LPJmL (Rost et al., 2008; Gerten et al., 2004). Besides crop yields, LPJmL delivers this water discharge value for each grid cell as a possible constraint for irrigation in MAgPIE. The information about irrigation and rainfed land use fractions is derived from a modification of the MIRCA2000 land use dataset (Portmann et al., 2010). More information on the methodology can be found in Fader et al. (2010).

3.2.2 Cost types

Four categories of costs arise in the model: production costs for livestock and crop production, yield increasing technological change costs, land conversion costs and intraregional transport costs. The model solution is derived by minimizing these four cost components on a global scale for the current time step.

In order to increase total agricultural production, MAgPIE can either invest in yield-increasing technological change or in land expansion (Popp et al., 2011a). The endogenous implementation of technological change (TC) is based on a surrogate measure for agricultural land use intensity (Dietrich et al., 2012). Investing in TC leads not only to yield increases but also to increases in agricultural land-use intensity, which in turn raises costs for further yield increases. Schmitz et al. (2010) related agricultural land-use intensity to empirical data on investments in TC based on a regression analysis. The data for agricultural Research & Development investments are from IFPRI (Pardey et al., 2006) and for infrastructure investments from GTAP (Narayanan and Walmsley, 2008). From the results they calculated a yield elasticity with respect to TC investments (ϵ_I^{yld}) of 0.27. Figure 2.5 in chapter 2.3.2 shows the validation of the resulting TC rates in MAgPIE compared with observed data from FAO.

Production costs in MAgPIE reflect factor costs for labour, capital, and intermediate inputs. To determine the influence of TC on production costs, a regional correlation analysis between yield and costs per area and yield and costs per production unit was conducted (Schmitz et al., 2010). Results of the correlation analysis indicated the existence of a positive correlation between yields and area-related production costs, but no correlation between yield and output-related production costs. Based on this result production costs per ton had been implemented as a constant input, which led to the linear relationship between production costs per area and yield.

The other alternative for MAgPIE to increase production is to expand cropland into non-agricultural land (Krause et al., 2009; Popp et al., 2011a). In this model version no policy restrictions are in place regarding the expansion of cropland. However, the expansion involves land-conversion costs for every unit of cropland, which account for the preparation of new land and basic infrastructure investments. Land conversion costs are based on country-level marginal access costs generated by the Global Timber Model (GTM) (Sohngen et al., 2009). Moreover, land expansion in MAgPIE is restricted by intraregional transport costs which accrue for every commodity unit as a function of the distance to intraregional markets. The value is dependent on the quality and accessibility of the infrastructure. Hence, the less accessible the land is, the higher are intra-regional transport costs, which leads to higher overall costs of cropland expansion. The data are based on GTAP transport costs (Narayanan and Walmsley, 2008) and a 30 arc-second resolution data set on travel time to the nearest large city released by the European Commission Joint Research Centre (Nelson, 2008). More information on the model framework is presented in a mathematical description of MAgPIE in Appendix 1.

3.2.3 International trade

We implemented international trade in MAgPIE by using flexible minimum self-sufficiency ratios at the regional level. Self-sufficiency ratios describe how much of the regional agricultural demand quantity has to be produced within a region. For instance, a ratio for cereals of 0.80 means that 80% of cereals are produced domestically, whereas 20% are imported. To represent the trade situation of 1995 we calculated the self-sufficiency ratios ($p^{sf}_{i,k}$) for each region i and production activity k from the food balance sheets of FAO for the year 1995 (FAOSTAT, 2010) (see Appendix 3).

We implemented two virtual trading pools which allocate the global demand to the different supply regions (Figure 2). The demand which enters the first pool is allocated according to fixed criteria. Self-sufficiency ratios determine how much is produced domestically, and export shares determine the share of each region in global exports. The export shares are generated for every crop for the year 1995 and are taken from FAO (FAOSTAT, 2010) (see Appendix 3). However, although the initial self-sufficiencies for this pool stay constant over time, the final self-sufficiencies do change since domestic demand and population change over time. The demand which enters the second pool is allocated according to comparative advantage criteria to the supply regions. The criteria, under given constraints like crop rotation or water availability, are biophysical yield, production costs and technological change leading to yield increase. This implies that the model optimizes supply with the goal of minimizing global production costs and produces in those cells where it is most economical compared to other cells.

The parameter p^{tb} (trade barrier reduction factor) defines the share of trade volume which flows into both pools. If p^{tb} is equal to 1, the total demand will be distributed to the supply regions according to fixed self-sufficiencies and export shares. If p^{tb} is equal to 0, the whole trade volume will end up in the second pool and is distributed according to comparative advantage criteria to the supply regions. The following equations demonstrate the same procedure in mathematical terms. Equation 3.1 shows the global trade balance, where the aggregated regional supply f^{prod} adjusted by the seed share

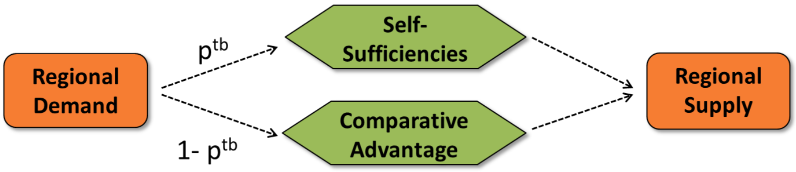

Figure 3.1: Trading pools in MAgPIE. The fixed pool allocates demand according to fixed criteria (self-sufficiency ratios and export shares). The free pool allocates it according to comparative advantage criteria.

f^{seed3} has to be equal or bigger than the aggregated regional demand f^{dem}.

$$\sum_i \frac{f^{prod}_{t,i,k}(x_t)}{1+p^{seed}_{i,k}} \geq \sum_i f^{dem}_{t,i,k}(x_t) \tag{3.1}$$

with x as the variable for production, i as region, t as time and k as production activity. Subsequently, we introduced excess demand and supply equations. The global quantity of excess demand p^{xd} for each production activity k is calculated by subtracting domestic demand (f^{dem}) from domestic production for the importing countries (self-sufficiency ratio $p^{sf} < 1$) (Equation 3.2). Domestic production is calculated by multiplying domestic demand with the self-sufficiency ratio. The calculated excess demand is distributed to the exporting regions according to their export shares p^{exshr} (Equation 3.3).

$$\left\{ p^{xd}_{t,k} = \sum_i f^{dem}_{t,i,k}(x_t)(1-p^{sf}_{t,k}) \quad : p^{sf}_{i,k} < 1 \right. \tag{3.2}$$

$$p^{xs}_{t,i,k} = p^{xd}_{t,k} p^{exshr}_{t,i,k} \tag{3.3}$$

The trade balance equation (3.4) assures that demand and supply are balanced at the regional scale. In the case of an exporting region, the regional supply has to be greater or equal than the domestic demand plus the exported quantity. In the case of an importing region, the regional supply has to be greater or equal than the domestic demand times the self-sufficiency. This holds true, if the trade barrier reduction factor p^{tb} is equal to one. If p^{tb} is equal to zero, the equation becomes zero and everything is solved via the global trade balance (Equation 3.1).

$$\frac{f^{prod}_{t,i,k}(x_t)}{1+p^{seed}_{i,k}} \geq p^{tb} \begin{cases} f^{dem}_{t,i,k}(x_t) + p^{xs}_{t,i,k} & : p^{sf}_{i,k} \geq 1 \\ f^{dem}_{t,i,k}(x_t) p^{sf}_{i,k} & : p^{sf}_{i,k} < 1 \end{cases} \tag{3.4}$$

[3]The seed share accounts for the produced quantity which is used as seeds for the next farming season

3.2.4 Greenhouse gas emissions

MAgPIE calculates greenhouse gas emissions of CO_2, CH_4 and N_2O resulting from land-use changes and agricultural activities. CO_2 emissions are calculated as the difference in carbon content between natural vegetation and managed crop production. CO_2 emissions from land-use change occur whenever natural vegetation is converted into cropland. The difference in the carbon stocks between both land-use types is released in the form of CO_2 emissions. Carbon emissions from soils are not captured. Carbon stocks are projected using the LPJmL model.

CH_4 emissions in MAgPIE have three possible sources. First, animal waste management systems (AWMS) are responsible for CH_4 emissions by the anaerobic decomposition of manure. In MAgPIE, this effect is influenced by temperature, the kind of livestock, and the development level of the region. Second, ruminant livestock, like cattle, sheep, or goats, produce methane by fermenting feed in stomach and intestine. Third, rice cultivation is responsible for CH_4 emissions from flooded fields. Besides the amount of rice cultivation, this emission type depends on water management practices and a specific regional factor. CH_4 emissions are estimated using the emission factors of the Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC, 1996).

N_2O emissions in MAgPIE have two possible sources. Like in the case of CH_4, one source is the AWMS which produces N_2O by denitrification and nitrification of animal excrements. In MAgPIE, this is dependent on the amount of livestock products and the type of livestock system. The second source is N_2O emissions from cultivated soils. These are directly affected by the kind of nitrogen fertilizer used (synthetic fertilizer, manure, crop residues and N-fixing crops). In addition, indirect effects occur through atmospheric deposition of NOx and NH_3 and through leaching of nitrogen fertilizer. N_2O emissions are estimated using the emission factors of the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC, 1996).

The emission values are given in CO_2-equivalent using their "global warming potential" (GWP). According to IPCC (2007), CH_4 contributes 25 times as much to global warming compared to CO_2. The factor for N_2O is 298. Further information on the detailed calculation of these emissions within MAgPIE is provided in Popp et al. (2010) and Popp et al. (2011b).

3.2.5 Scenarios

We consider three scenarios: (1) The reference scenario ($reference$) keeps current trade patterns constant over time until 2045. (2) The policy scenario (*policy*) follows a historically derived pathway of trade liberalisation. Taking into account various literature sources we decided that a 10% trade barrier reduction each decade until 2045 reflects a realistic policy scenario for the future (Healy et al., 1998; Conforti and Salvatici, 2004)[4]. This is also supported by the general trade study of Dollar and Kraay (2004), who found

[4] In the course of the Uruguay Round, tariff lines have been reduced at least by 15% for developed countries, 10% for developing countries, and 0% for least-developed countries (Healy et al., 1998).

Table 3.1: Trade barrier reduction factor in different trade scenarios over time

Scenario	1995	2005	2015	2025	2035	2045
reference	1	1	1	1	1	1
policy	1	0.9	0.81	0.73	0.66	0.59
liberalisation	1	0.8	0.6	0.4	0.2	0

a 22% tariff cut for non-globalising countries, 11% for globalising countries, and 0% for rich countries between the 1980s and 1990s[5]. (3) The liberalisation scenario (*liberal*) allows for full trade liberalisation in 2045 by reducing the trade barrier reduction factor to zero over time. The assumption here is that the world will be fully liberalised in 2045 and everything is traded according to comparative advantage criteria. In MAgPIE, liberalising trade implies the reduction of boarder measures, like tariffs, quotas, export restraints and any other non-tariff barrier. Internal measures, like producer subsidies, are not explicitly captured in MAgPIE. Hence, in the case of trade liberalisation all trade distorting measures are removed and goods can be traded freely.

The scenarios differ by changing the trade barrier reduction factor p^{tb}, a parameter that describes the share of demand which is traded according to fixed self-sufficiencies. Table 3.1 gives the values for p^{tb} in each period and scenario. As mentioned, in the reference scenario demand is traded according to fixed rules. Therefore, the value for p^{tb} is 1 in all time steps. In the policy scenario it changes and the factor is reduced by 10% in each decade. In the liberalisation scenario p^{tb} is reduced continuously towards 0 in 2045, when demand is fully traded according to comparative advantage criteria.

3.2.6 Sensitivity analysis

Due to space limitations and scope of the paper, we focus the sensitivity analysis on the two most important drivers, namely the rate of technological change (TC) and the rate of land expansion. We chose the estimated parameter for yield elasticity and intra-regional transport costs for the sensitivity test. Firstly, for TC, we base our assumption on the endogenous implementation presented by Schmitz et al. (2010) and in chapter 3.2.1. From a regression between investments in TC and the associated yield change, a yield elasticity with respect to TC investments (ϵ_{Inv}^{Yld}) of 0.27 is derived. In the literature a value of 0.296 is given (Nelson et al., 2009). For the sensitivity analysis we chose two extreme scenarios, in which we set the elasticity to 0.32 ($cheapTC$) and 0.22 ($expensiveTC$). We conducted numerous tests on possible alternative regression results and in no case the elasticities were higher than 0.31 or lower than 0.24. Therefore, we choose a range of +0.05 and -0.05 around 0.27 as extreme values. In the first case,

[5]"Rich countries refer to the 24 OECD economies before recent expansion plus Chile, Hong Kong, Korea, Taiwan, and Singapore. Globalisers refer to the top one-third in terms of their growth in trade relative to GDP between 1975-9 and 1995-7 of a group of 72 developing countries for which we have data on trade as a share of GDP in constant local currency units since the mid-1970s. Non-globalisers refer to the remaining developing countries in this group." (Dollar and Kraay (2004), p. 23)

investments in TC are more profitable and in the second case it is the other way round and more expensive to reach a certain yield level.

Secondly, we test the intra-regional transport cost level, which is crucial for land expansion and determines how costly it is for MAgPIE to subdue new cropland. As explained in chapter 3.2.2, the data are based on transport costs and the transport time to the next non-cropland cell, which includes distance and the quality of infrastructure. For the sensitivity analysis we halved the costs (*lowtrans*) and doubled them (*hightrans*), which are extreme scenarios on both ends.

3.3 Results

3.3.1 Trade balances

Trade balances (in million tons) are calculated by taking the difference between exports and imports of a region. We decided to focus on the most important crop groups for international trade (cereals, oilcrops, sugar, vegetables/fruits, and meat).

Figure 3.2 shows trade balances, displayed as netexports, for cereals (incl. rice) and oilcrops. The ten world regions are distinguished by different colours. The three scenarios are compared in each graph (reference scenario on the left, policy scenario in the middle and liberalisation scenario on the right). The three bars in each scenario cover the three time spans: 2005-2020 (A), 2020-2035 (B) and 2035-2050 (C). In the reference scenario, EUR and NAM dominate the market for cereal exports. The imports are shared among the other regions, led by MEA. This situation changes in the other two scenarios when PAO, AFR, LAM, and FSU join the export group at the expenses of EUR, which becomes partly a net importer. On the import side CPA and SAS increase their quantities most. The average global trade volume in cereals in the years 2035 to 2050 increases to over 800 mio. tons in the liberalisation scenario (compared to around 450 mio. tons in the reference scenario). The export market for oilcrops is mostly dominated by NAM and LAM. With more trade, LAM strongly increases its export volume. In the last time step, LAM increases its export from 30 mio. tons to around 80 mio. tons. In the liberalisation scenario, SAS and EUR join the export group with small shares. On the import side CPA and AFR face the highest increases over time and with more trade.

Appendix 4 shows the trade balances for sugar, vegetable/fruits, and meat. Concerning the sugar market, LAM dominates the market with an export share of around 75%. This increases under trade liberalisation to more than 90% in the last time step (2035-2050). Imports increases continuously across the importing regions, especially in CPA and AFR. Vegetables and fruits will mostly be exported by CPA and to a lower extent by SAS under increased trade. Europe will continue to be the leading importer. For meat, CPA will dominate the export market with shares of over 95% under trade liberalisation.

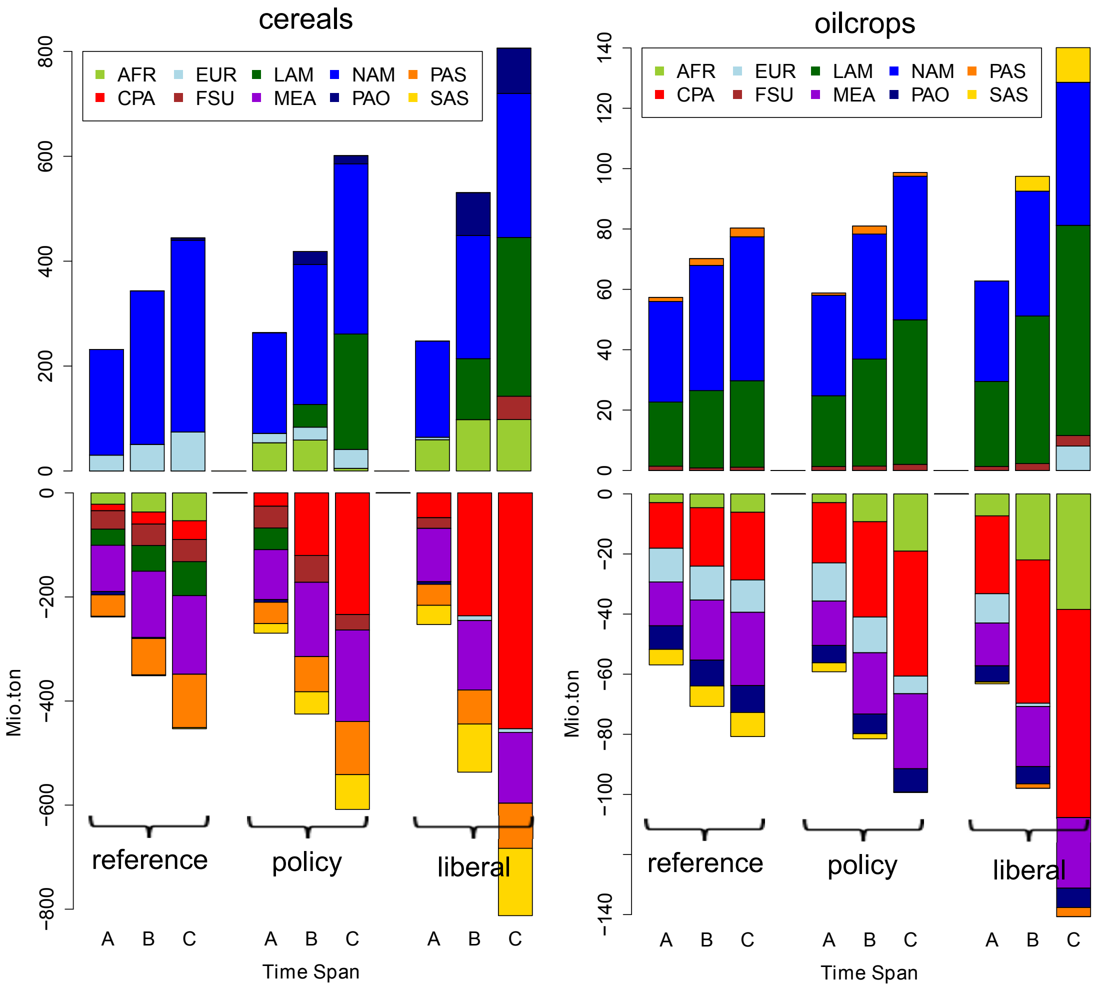

Figure 3.2: Net export quantities of cereals (incl. rice) and oilcrops for ten world regions in three trade scenarios and for three time spans (A = 2005-2020; B= 2020-2035; C= 2035-2050)

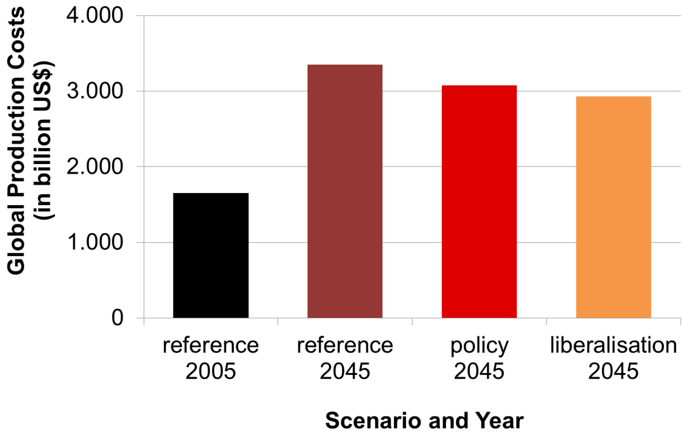

Figure 3.3: Global annual production costs in the reference scenario in 2005 and in each scenario in 2045

3.3.2 Global costs and food scarcity

MAgPIE is a mathematical programming model which minimizes global agricultural production costs. These costs reflect the factor costs of labour, capital, and intermediate inputs. Figure 4 shows the global annual production costs for the reference scenario in 2005 and 2045 and the two increased trade scenarios in 2045.

In 2005, MAgPIE starts with a value of 1.65 trillion US$. As a validation of this output we took the agricultural value-added output from the World Development Indicators[6]. The measured value amounts to 1.54 trillion US$ (average of 2004-2006) (World Bank, 2011). Although both figures are very close, we have to account for some differences. In contrast to the measured data, the model data include intermediate inputs (global share of 22%) but no land data (global share of 17%). In addition, MAgPIE production does not account for forestry, hunting and fishing which would also lead to higher total production costs. Hence, although the data are not fully comparable, they should be quite similar. The production costs increase over time in all three scenarios. In the reference scenario, costs amount to 3.35 trillion US$ in 2045. More liberalisation leads to lower global production costs. The costs in the policy scenario decrease to 3.07 trillion US$ and in the liberalisation scenario to 2.93 trillion US$ in 2045.

In Figure 3.4 we present a scarcity index for agricultural products. The index shows marginal costs of food production which indicate the costs of one additional unit of food. A rising index expresses that food production is becoming more expensive. In this analysis we obtain a sharp increase of the index by 80% until 2045 in the reference scenario. In the policy scenario marginal costs increase continuously by about 5 to 10%

[6] The agricultural value-added output measures the output of the agricultural sector less the value of intermediate inputs. The agricultural sector corresponds to ISIC (International Standard Industrial Classification) division 1-5 (Revision 3) and comprises value added from cultivation of crops and livestock production as well as forestry, hunting, and fishing.

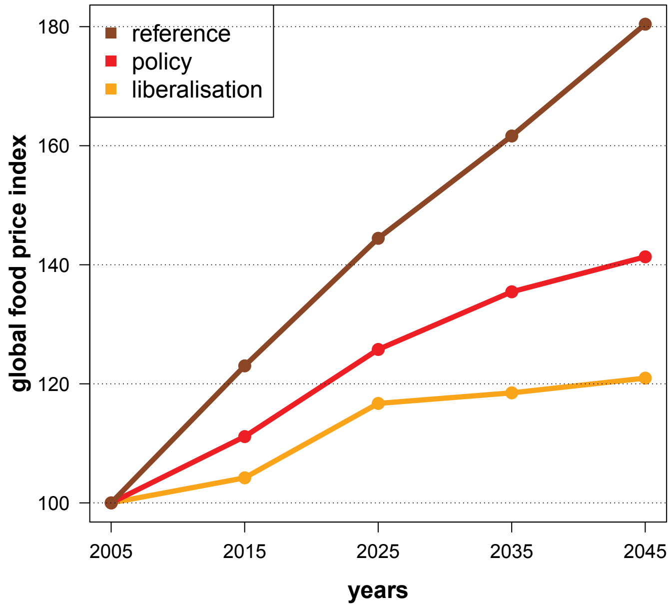

Figure 3.4: Scarcity Index for agricultural products over time in each scenario

per decade and end up at 140 index points in 2045. For the liberalisation scenario we obtain a slow and uneven increase to an index value of 120 in 2045.

3.3.3 Technological change rates

Figure 6 shows average annual technological change (TC) rates of the ten world regions, which are required to fulfil food demand over the period of 2005-2045. In all cases, except LAM, PAO and PAS, the TC rates decrease with increasing trade. MEA and SAS face the strongest decreases. In MEA the required TC rate drops from 2.1% in the reference to 0.5% in the liberalisation scenario. In SAS it reduces from 2.0% to 1.1%. AFR and CPA show slight decreases in the policy scenario and the liberalisation scenario. The opposite holds true for LAM where the demand for TC slightly increases. In PAS and PAO, TC rates do not change between the different scenarios. In addition, the global average TC rates decline from 1.2% (*reference*) to 1.0% (*policy*) and 0.9% (*liberalisation*).

3.3.4 Land use change and related carbon emissions

Besides technological change MAgPIE has also the option of expanding cropland in order to increase production. Figure 3.6 illustrates expansion of cropland into forest from 2005 to 2045. The map shows how much of each cell (in land use shares) is

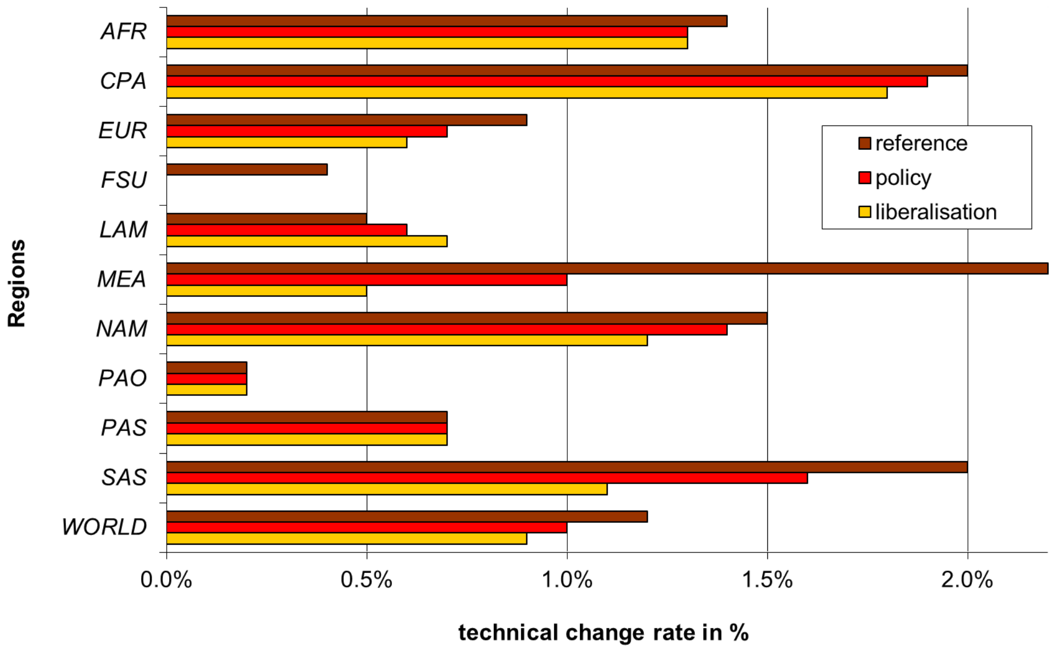

Figure 3.5: Average annual technical change from 2005 to 2045 for the 10 MAgPIE regions and globally aggregated ($WORLD$). The brown bars represent the rates under the constant trade scenario ($reference$), the orange bars the moderate trade liberalisation scenario ($policy$), and the yellow bars the full liberalisation scenario ($liberal$).

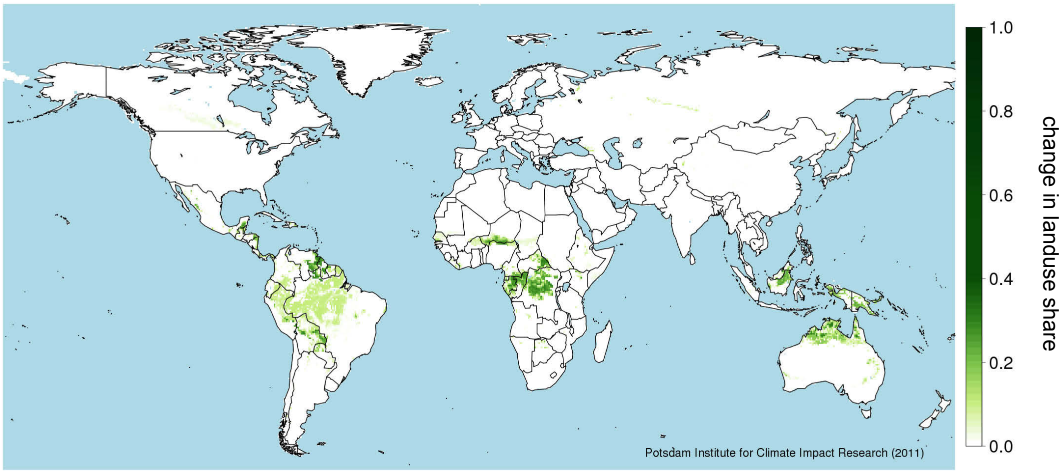

Figure 3.6: Relative rate of cropland expansion (change in land use share of all crops) per grid cell (0.5°) in the reference scenario between 2005 and 2045

converted from forest to cropland in this period. The most affected area will be the Central African rainforest, followed by the Amazonian Rainforest and the rainforest in Indonesia and North Australia. Some land expansion takes place in the Savannah Region of West Africa and in Mexico.

Figure 3.7 illustrates the difference in cropland expansion between the reference and policy scenario (top) and the reference and liberalisation scenario (bottom). Positive values (green colour) indicate that MAgPIE uses more cropland in the featured scenario compared to the reference scenario. If the value is negative (orange/red colour), MAgPIE uses less cropland. In both maps total cropland expansion increases and the expansion in Africa is almost constant. In the policy scenario between 2005 and 2045 more area in the Amazonian Rainforest is converted into cropland (around 170 mio. ha). In the liberalisation scenario this amount increases further by 20 mio. ha. Some small increases in cropland are found in Indonesia, whereas in both trade scenarios less area is converted in the North of Australia.

Expansion of cropland into forest results in significant amounts of CO_2 emissions (Figure 3.8). The rainforest regions LAM, AFR, and PAS emit most CO_2 until 2045. The emissions in AFR stay almost on a constant level throughout all scenarios. In LAM around 25% more carbon emissions are produced under the policy scenario and almost 60% under the liberalisation scenario. In PAS the amount of CO_2 emissions decreases with more trade; from 30 Gt in the reference scenario, to 28 Gt in the policy scenario and to 24 Gt in the liberalisation scenario. In total, cumulated CO_2 emissions between 2005 and 2045 increase from 175 Gt in the reference scenario to 226 Gt in the policy scenario. In the liberalisation scenario, emissions increase further to 249 Gt.

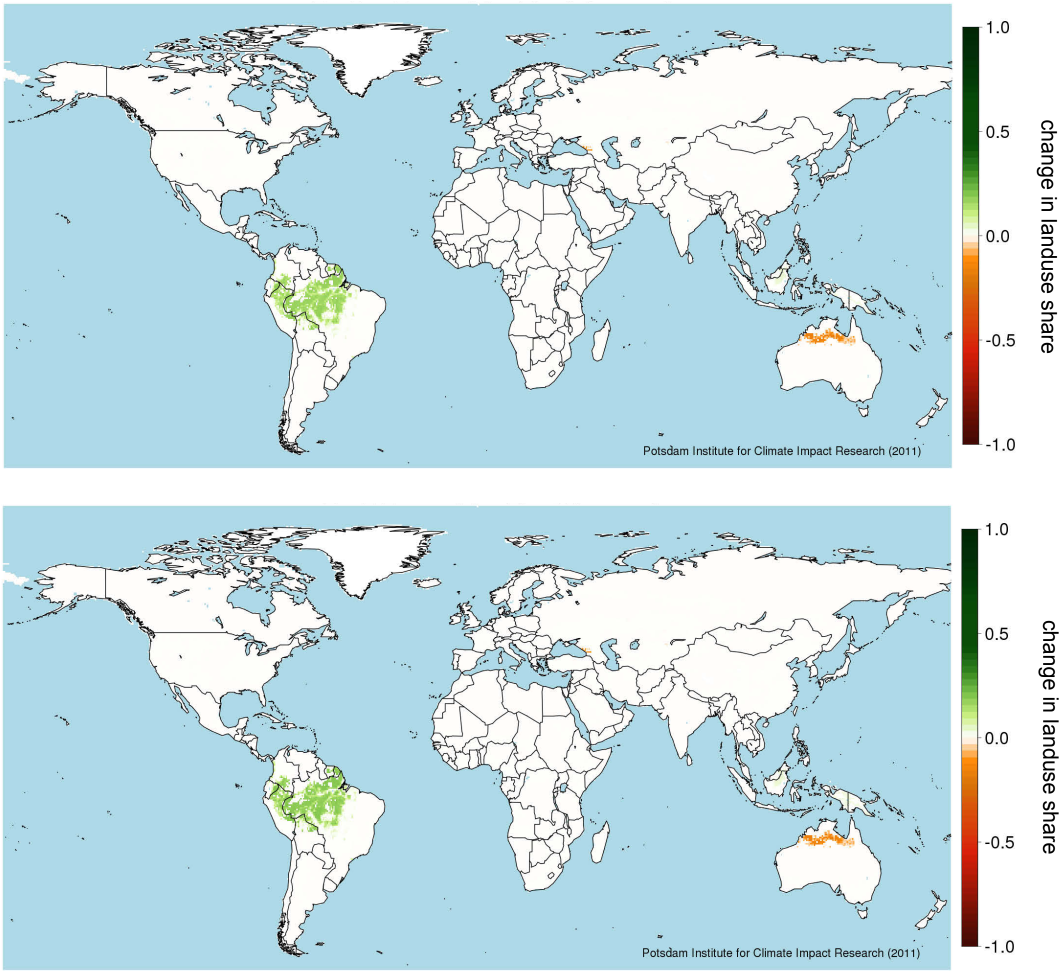

Figure 3.7: Relative change in land use share of all crops per grid cell (0.5°) between reference and policy scenario (top) and between reference and liberalisation scenario (down) in the period of 2005 to 2045

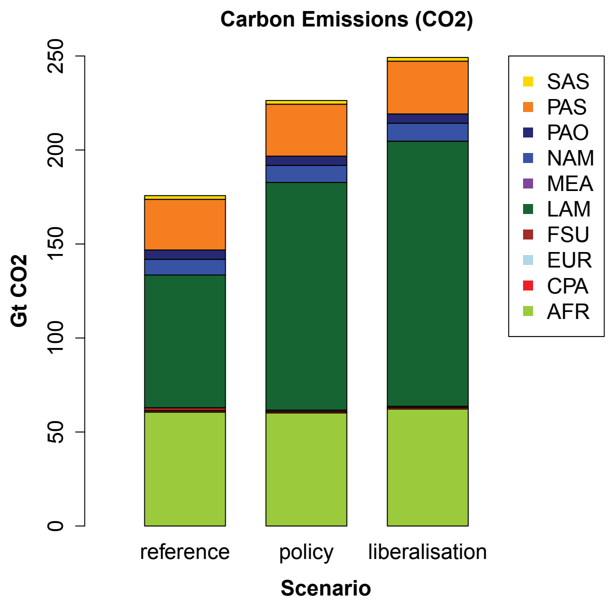

Figure 3.8: CO_2 Emissions from deforestation in three trade scenarios (2005-2045)

3.3.5 Non-CO_2 emissions

MAgPIE provides results of non-CO_2 emissions (CH_4 and N_2O) from livestock, rice production and soil fertilization (see section 3.2.4). On a global scale, we find a small increase in non-CO_2 emissions with more trade. Total emissions amount to 361 Gt CO_2-equivalent emissions in the reference scenario, 362 Gt in the policy scenario and 364 Gt in the liberalisation scenario. Whereas the global amount of the single emission types does not differ largely, the regional distribution is very dynamic.

Figure 3.9 shows the regional disaggregation of total emissions displayed in CO_2-equivalent emissions. The main driver in terms of non-CO_2 emissions is the livestock system and the kind of livestock. Both are responsible for CH4 and N2O emissions from fermentation and animal waste management. In both cases, most changes occur in CPA, due to a large increase in livestock production and in AFR, where livestock production is decreased. In CPA emissions from fermentation and animal waste management increase by around 70% in the policy scenario and by around 150% in the liberalisation scenario compared to the reference scenario. At the same time emissions decrease in AFR by 26% in the policy and 53% in the liberalisation scenario. Furthermore, emissions decrease in FSU, LAM, MEA, NAM, PAS, and SAS.

Emissions from rice cultivation and crop management play a minor role on a global scale. Only in PAS rice emissions are the major sources, accounting for more than 50% of the emissions in this region. In general, emissions from rice cultivation are mostly emitted in the Asian Regions (CPA, PAS, SAS). On a global level they increase continuously with more trade. On the regional level, emissions decrease slightly with

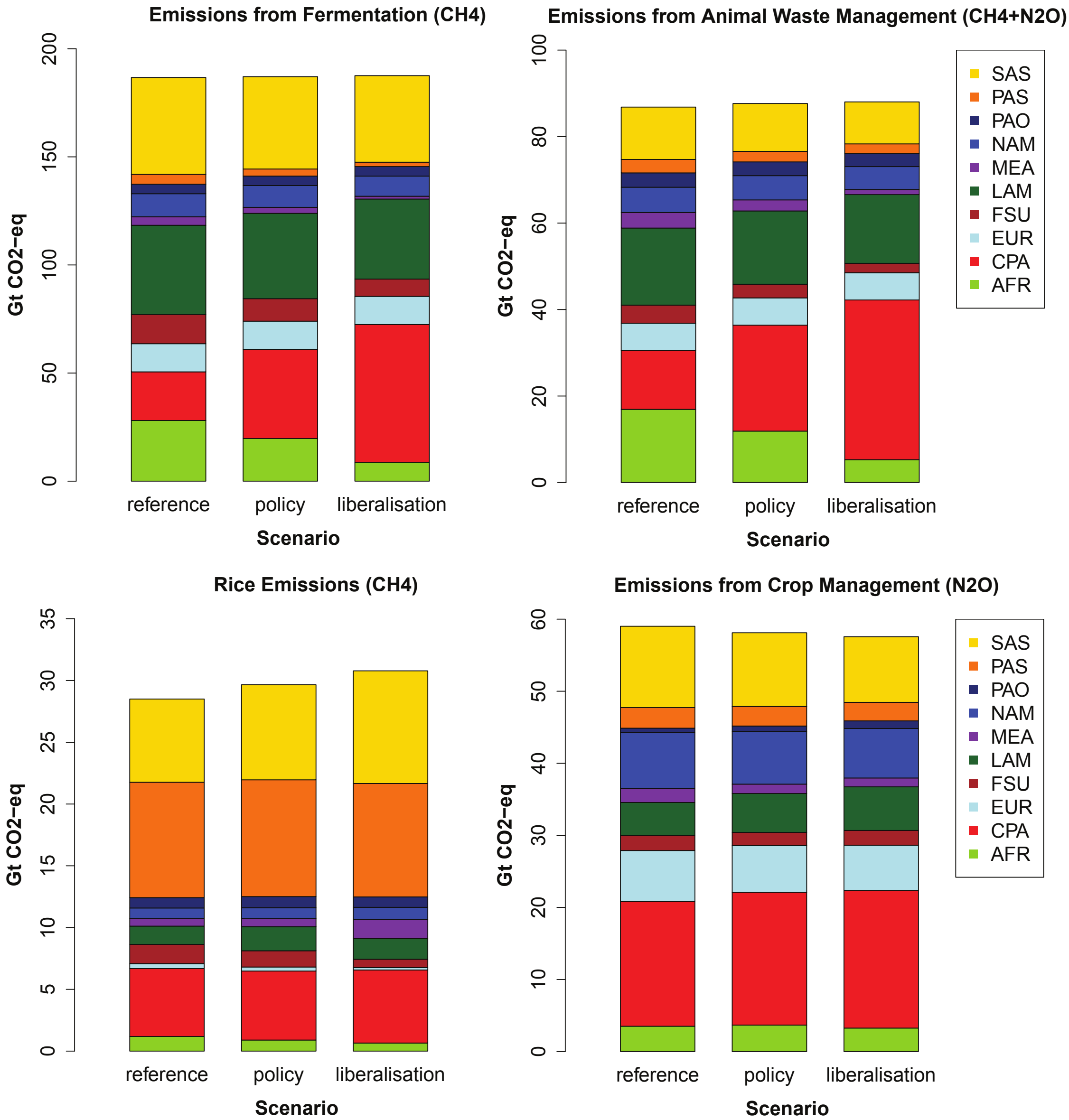

Figure 3.9: Non-CO_2 Emissions (in CO_2-equivalent) for the three trade scenarios (2005-2045)

more trade in almost all regions except of SAS and MEA, which are the main driver for the overall increase. In the case of N2O emissions from crop management the global picture looks different, since CPA, EUR, FSU, NAM and SAS reduce emissions with more trade and CPA and LAM increase their emission level. On global level, the emissions decrease slightly. Figure 6 in Appendix 4 shows the spatial distribution of non-CO_2 emissions for the three trade scenarios. In the reference scenario, most emissions occur in the Asian regions, especially in North-East China, North India, and the Pacific Islands (Malaysia and Indonesia. Russia, Australia, and Sub-Sahara Africa have the lowest emission levels. Under increased trade emissions increase slightly in South America and China and decrease slightly in USA and Pacific Asia.

3.3.6 Global balance

Figure 3.10 shows the joint picture of environmental and economic impacts due to increased trade on a global scale (policy and liberalisation scenario). Economic benefits are represented by the saved costs of agricultural production and environmental impacts are represented by additional GHG emissions (in CO_2 equivalent). The values are aggregated over the ten world regions and over the whole time period (2005-2045).

In the policy scenario 6.5 trillion US$ are saved from 2005 to 2045 but at the same time 52 Gt of additional GHG emissions (in CO_2-equivalent) are emitted. This means for every saved US$ in the agricultural production sector around 7.9 kg GHG emissions are generated. Comparing the liberalisation scenario with the reference scenario, around 11 trillion US$ are saved and around 76 Gt of additional GHG emissions are produced. This decreases the ratio to 6.9 kg CO_2-equivalent per saved US$ production costs.

3.3.7 Sensitivity analysis

The results of the sensitivity analysis are summarized in Table 3.2. The differences in cropland vary between -7% and +3%. Increases in cropland are obtained in the scenarios with low yield elasticity of TC investments (expensiveTC) and with low intra-regional transport costs (lowtrans) and decreases in the other sensitivity tests. The same holds in terms of total GHG emissions, although their changes are larger, ranging from -10% (cheapTC liberal) to +5% (lowtrans liberal). Total costs decrease in the cheapTC and lowtrans variant and increase in the expensiveTC (up to 9%) and hightrans (up to 16%) variant. If we set additional GHG emissions in perspective to saved costs between the reference scenario and the two liberalisation scenarios, we observe a variation between 1.3 and 8.9 kg CO_2-eq/US$.

Table 6(a) and 6(b) in Appendix 5 show the regional disaggregated results for land expansion and TC in the respective sensitivity runs. Most regions show changes of less than 10%. Exceptions are LAM, PAO, and PAS. LAM converts about 35% less land into cropland in the case of high yield elasticity (cheapTC) and about 20% less with high transport costs (hightrans). In PAO up to 80% additional land is converted in the other two sensitivity tests (expensiveTC and lowtrans). In PAS between 30 and 40% less land is converted with high transport costs and about 20% more land with low

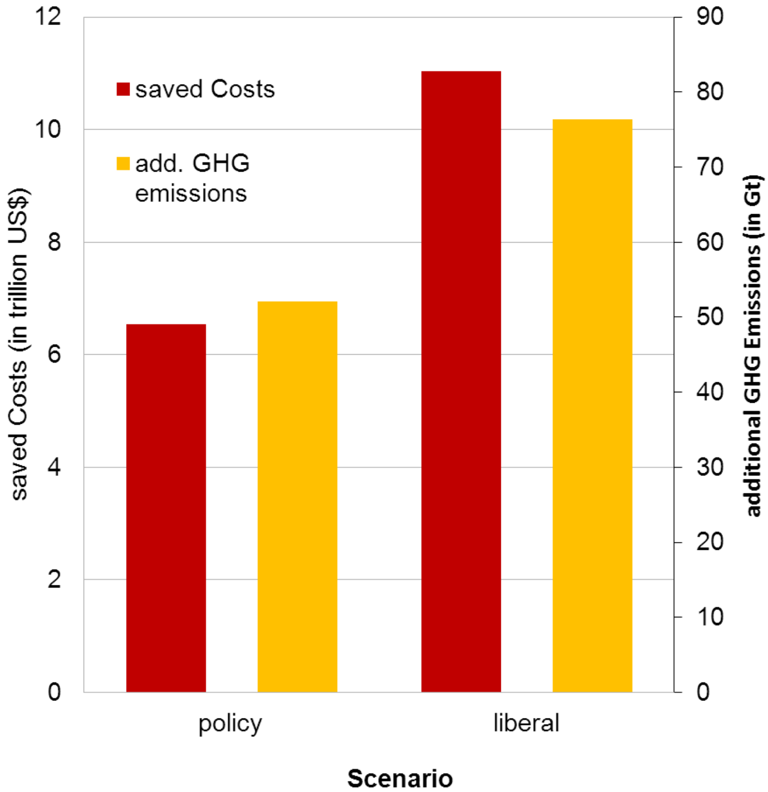

Figure 3.10: Global cost-savings (red bars) and additional GHG emissions (yellow bars) from the policy and the liberalisation scenario compared to the reference scenario over the period 2005 to 2045.

Table 3.2: Results of standard model version in comparison with sensitivity runs. Percentage numbers are the difference between sensitivity run and the respective run of the standard model version.

model run		**Total Cropland** *(in million ha)*		**Total Emissions** *(in Gt CO_2-eq.)*		**Total Costs** *(in trillion US$)*		**Add. emissions per saved costs** *(kg CO_2-eq./US$)*
standard-model	*refer*	1,950		533		100.7		-
	policy	2,105		585		94.1		7.9
	liberal	2,127		609		89.6		6.9
cheap-TC	*refer*	1,930	-1%	527	-1%	95.3	-5%	-
	policy	1,947	-7%	533	-9%	90.7	-4%	1.3
	liberal	1,993	-6%	551	-10%	87.0	-3%	2.9
expen-siveTC	*refer*	1,957	0%	536	1%	109.6	9%	-
	policy	2,162	3%	601	3%	98.6	5%	5.9
	liberal	2,187	3%	633	4%	92.2	3%	5.6
low-trans	*refer*	1,973	1%	544	2%	92.9	-8%	-
	policy	2,149	2%	605	3%	86.0	-9%	8.9
	liberal	2,197	3%	638	5%	81.7	-9%	8.4
high-trans	*refer*	1,885	-3%	511	-4%	115.2	14%	-
	policy	2,015	-4%	551	-6%	109.1	16%	6.5
	liberal	2,021	-5%	560	-8%	104.3	16%	4.5

transport costs. Concerning TC rates we observe large increases with higher transport costs in LAM and lower TC rates with lower transport costs in PAO and PAS.

3.4 Discussion

Agricultural trade and its various impacts on climate change faces growing interest and importance, especially regarding international trade and climate negotiations (Tamiotti et al., 2009). This study presents a new approach to tackle this issue by using a spatially explicit global land use model that takes environmental as well as economic indicators into account.

In terms of economic impacts, model results show that further trade liberalisation leads to a shift in export shares in favour of regions with comparative advantages in agriculture. These regions benefit at the expense of highly protected regions. For cereals as well as oilcrops, North America and Europe export less if trade becomes more liberalised. This indicates how much both regions are currently affected by their protective agricultural policies (Gibson et al., 2001). Their lower production level in 2045 is mainly due to a drop in technological change (TC) rates in these regions, whereas cropland for cereals and oilcrops is almost not affected. South Asia faces a sharp drop in TC rates. Due to scarce resources and a low comparative advantage, the region imports more and has a lower pressure to increase productivity. In contrast, China imports more due to its increasing demand but TC rates decrease only slightly. Australia, Sub-Saharan Africa, and Latin America are the regions, which take most of the export share from Europe and North America due to their comparative advantage in cereal production.

Overall, Latin America is the region which increases its exports most. In addition to more cereal exports, it will increase its share on the vegetable oil market under more trade liberalisation. The abundant land resource and increasing TC rates lead to a tremendous production increase. In the reference scenario cropland is already expanded from 175 mio ha. in 2005 to 353 mio. ha in 2045. In the policy scenario it increases to 525 mio. ha and in the liberalisation to 546 mio. ha. A similar trend is found by DeFries et al. (2010), who observe a strong correlation between trade activity and deforestation rates in Latin America.

On a global scale the results demonstrate that increased trade liberalisation will lead to lower global costs of food production. Model results show that around 6% (5.4 trillion US$) will be saved in the period of 2005 to 2045 by applying the policy scenario and 10% (9.4 trillion US$) in the liberalisation scenario. Moreover, our model shows that trade liberalisation leads to a much slower increase in the food scarcity index. This is supported by Federico (2005), who showed that in the past increased trade contributed largely to a reduced pressure on food prices. Nonetheless, these model results do not reflect important policy considerations like food security or domestic socio-economic and environmental implications. In general, we implemented international trade barriers in a rather broad manner, without differentiating between specific measures, like quotas, subsidies, or tariffs. A detailed representation of trade policy is not done in our spatially explicit modelling framework since it would overstrain the model regarding computing capacity.

Regarding environmental impacts we focus on land use change and greenhouse gas emissions as the main indicators in this study. According to FAO 71 million hectares of land have been converted into cropland in the period of 1990-2000 and 225 mio. ha in the period of 1960-2000 (FAOSTAT, 2009). Our model results show that without further regulation of deforestation, future cropland expansion mainly takes place in ecologically sensitive areas of the tropical rainforest. In the reference scenario total cropland expansion (2005-2045) in the three main rainforest areas, the Amazonian rainforest (178 mio. ha), the Central African rainforest (137 mio. ha) and the rainforest on the Pacific islands (37 mio. ha) amounts to 410 mio. ha or 23% of the global cropland area in 2005. Under trade liberalisation this increases further by 175 mio. ha (policy) and 198 mio ha (liberalisation), mainly in the Amazonian rainforest. Similar results are found by van Meijl et al. (2006) and Eickhout et al. (2009), who show that trade liberalisation leads only to small land-use shifts in Europe but dramatic shifts in developing regions.

CO_2 emissions from tropical deforestation are an important contributor to climate change since tropical forest consists of around 50% more carbon per unit area than any other forest system and faces the highest deforestation rates (Houghton, 2003). At least 25% of all anthropogenic carbon emissions during the 1980s and 1990s origin from tropical deforestation (Malhi and Grace, 2000; Houghton, 2003) and currently they account for almost 20% of total GHG emissions (Grainger, 2008; Gumpenberger et al., 2010). In MAgPIE, the conversion of previous intact forest leads to 175 Gt CO_2 emissions in the period from 2005 to 2045. Additional trade in the future increases emissions from deforestation due to further expansion in Latin America (mainly Brazil). Total carbon emissions rise by 50 Gt CO_2 in the policy scenario and 74 Gt in the liberalisation scenario until 2050 compared to the reference scenario. Total non-CO_2 emissions amount to 361 Gt CO_2 in the reference scenario and it increases only slightly with more trade. In terms of regional distribution, emissions in China rise since livestock production shifts from Africa to China due to comparative advantages. Although domestic demand for livestock products increases considerably, China will dominate the export market for meat products under more liberalisation.

In general, our overall results on emissions, except for carbon emissions, in the reference scenario are similar to results of a comparable study of Verburg et al. (2009). They report average annual emissions for their baseline scenario between 2000 and 2005 of 0.8 billion tons for CO_2, 3 billion tons for CH_4 and 1.2 billion tons for N_2O. Our corresponding figures for 2005 are 5.9, 3.8, and 1.9, respectively. However, since they assume full liberalisation already by 2015 the timing of emissions differs considerably. Whereas in their study CO_2 emissions increase until 2015, but are reduced until 2030 and until 2050, in our case CO_2 emissions increase constantly but with lower rates towards the end. Therefore, especially in Latin America, land will be cleared much faster, if trade will already be liberalised by 2015. Regarding non-CO_2 emissions Verburg et al. (2009) report similar mixed results as in our study. Whereas CH_4 emissions increase under trade liberalisation by around 4-5% (mainly due to Brazil), N2O emissions decrease slightly. In our study the increase in non-CO_2 emissions on a global level is moderate but a major reallocation between different regions takes place. Emissions in China increase due to the increase in livestock production, whereas Africa, Europe, and South/Pacific Asia decrease their emission levels from non-CO_2 sources. In Latin America, emissions increase only over time but not with more trade liberalisation.

Bringing environmental and economic aspects together, our result is that economic benefits are generated at the costs of the environment. If we just consider additional GHG emissions produced by increased trade (and ignore other local environmental damages), it amounts to 52 Gt of additional GHG emissions in the policy scenario and more than 76 Gt in the liberalisation scenario. The figures are mainly triggered by increased CO_2 emissions from deforestation in Latin America since non-CO_2 emissions do not change remarkable on the global level. To be more certain about the results we have conducted a sensitivity analysis on two key parameters in this process. Although we have chosen extreme values for these parameters, the results of the sensitivity runs show only moderate changes. If the yield elasticity of TC investments is lower or intra-regional transport costs are reduced, cropland and GHG emissions are increased by up to 5% since TC investments are less beneficial and land expansion gets cheaper, respectively. The opposite happens in the other two sensitivity tests, in which cropland and GHG emissions are reduced between 1 and 10%. In general, we obtain that the model behaves moderately with respect to changes in technological change and land expansion costs.

From the generated benefits in both scenarios (cost-savings due to increased trade) the additional GHG emissions could be easily compensated. The current price of CO_2 is around 10-20 US\$/tCO_2. Future projections about the CO_2 price are highly uncertain but are simulated to be in the range of 100 to 300 US\$/tCO_2 (Durand-Lasserve et al., 2010). Our model simulation leads to an ability to pay of up to 126 US\$/tCO_2 in the policy scenario and 145 US\$/tCO_2 in the liberalisation scenario. However, both figures do not consider several aspects which would decrease the values. First, we ignore other, more local environmental damages generated through increased trade (e.g. loss of biodiversity or environmental services). Second, not all emissions are considered in our calculation. Our modelling approach does not include transport-related emissions which would lead to an increase under trade liberalisation (Hummels, 2009). The same holds for non-CO_2 emissions from chemical fertilizer and pesticide production, which are likely to increase under trade liberalisation as well (SCBD, 2005). Finally, the saved production costs do not include international transport costs and other trade related costs, which would reduce the amount of saved costs. On the other side, there are indirect effects which likely decrease the amount of environmental damage with higher income induced by more trade. A first positive effect might be improvements regarding lower emission technology induced by higher income and more international competitiveness (Lucas et al., 2007). However, an often claimed spillover effect of environmental efficiency from developed to developing countries can only be partly confirmed regarding CO_2 and SO_2-efficiency (Perkins and Neumayer, 2009). A second and more deeply studied effect is illustrated by the Environmental Kuznets Curve, which is a U-shaped curve showing the relationship between income and certain environmental measures (Grossman and Krueger, 1993). Grossman and Krueger (1993) were the first to show that trade liberalisation increases the average income level, which leads to the demand of more environmentally friendly goods. Several studies have confirmed this view for air pollution which has a local effect, like SO_2 or NOx (for an overview, see Dasgupta et al. (2002) but not for global emissions, like CO_2 due to the free-rider problem (Frankel and Rose, 2005; Chintrakarn and Millimet, 2006; Kellenberg, 2008). Only recently Frankel (2009) showed that at a very high income level CO_2 emissions might decrease as well.

3.5 Conclusion

Synthesizing economic and environmental indicators brings us to the conclusion that most of the saved economic costs of trade liberalisation are achieved at the expense of environment and climate. Latin America reaches its increasing export share by converting large parts of the Amazonian rainforest into cropland at low costs. China generates globally most of the non-CO_2 emissions due to rising livestock demand in the region.

As both, climate change mitigation and trade liberalisation, have to be negotiated on a global scale, a major objective for future negotiations should be to account for these environmental and climate externalities and impose the related costs on the produced goods. As Brewer (2010) points out, several interactions between both fields, like lower tariffs on climate-friendly goods or biofuel trade policies, are already in place. More collaboration is needed in order to reduce situations when countries gain from trade but damaging the environment at the same time. Since most of the regions where these costs occur are developing countries, compensation policies have to be developed or further improved. Our analysis shows that regions which gain from increased trade are able to pay a sufficient portion of their benefits to account for related environmental damages like deforestation and GHG emissions. An emerging compensation scheme is REDD (Reduced emissions from deforestation and forest degradation), where compensation to countries is paid, if they guarantee protection of the rainforest (Ebeling and Yasue, 2008; Miles and Kapos, 2008). Although REDD has space for improvement, WTO and climate negotiations should adopt similar set-ups in order to cope with negative environmental impacts.

Another important policy implication is the investment into technological change. Higher productivity will lower the pressure on converting further forest land into cropland. Although the need has increased, investments into agricultural Research and Development have slowed down in the past decades resulting in lower agricultural yield growth (Alston et al., 2009). As a consequence, governments are advised to invest more and early into climate and environmentally friendly technological change in order to reduce the pressure on land and the environment for future generations.

4 Trade and deforestation - Global interactions and related policy options[1]

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Abstract

The extensive clearing of tropical forests throughout past decades has been partly assigned to increased trade in agricultural goods. Since further trade liberalisation can be expected, remaining rainforests are likely to face additional threats with negative implications for climate mitigation and the local environment. We apply a spatially explicit economic land use model coupled to a biophysical vegetation model to examine linkages and associated policies between trade and deforestation in the future. Results indicate that further trade liberalisation leads to an expansion of deforestation in Amazonia due to comparative advantages of agriculture in South America. Globally, around 36 million ha of forest would be cleared additionally, leading to around 23 Gt additional CO_2 emissions until 2050. By applying different forest protection policies those values could be reduced substantially. Most effectively would be the inclusion of avoided deforestation into a global emission trading scheme. Carbon prices corresponding to the concentration target of 550 ppm would prevent deforestation after 2020. Investing in agricultural productivity reduces pressure on tropical forests without the necessity of direct protection. In general, additional trade-induced demand from developed and emerging countries should be compensated by international efforts to protect natural resources in tropical regions.

[1] Reprinted version from Schmitz, C., H. Lotze-Campen, A. Popp, M. Krause, J.P. Dietrich, and C. Müller (2012), Trade and deforestation - Global interactions and related policy options, *under review for Ecological Economics.*

4.1 Introduction

Throughout the past three decades tropical deforestation has contributed between 12% and 25% to worldwide greenhouse gas emissions (Houghton, 2003; Fearnside and Laurance, 2003; van der Werf et al., 2009). Depending on methodology and data sources, total release of carbon from forest loss in the 1990s varies between 0.5 and 2.2 PgC per year and has increased considerably since the 1950s (Ramankutty et al., 2006). Besides generating carbon emissions, deforestation leads to socio-economic damages for the local population (Barraclough and Ghimire, 2000), reduced water cycling (Fearnside, 2005), increased flood risks (Bradshaw et al., 2007), disruptions of the local climate (Costa and Foley, 2010) and severe losses of biodiversity (Gorenflo and Brandon, 2005). From FAO country studies it is assessed that since the 1980s on average around 13 million ha of forest area has been lost every year (Ramankutty et al., 2006; FAO, 2010).

Cropland expansion is considered as one of the key drivers behind tropical deforestation. The World Bank estimated that 60% of deforestation is caused by an increase in agricultural land (World Bank, 1991). A more recent study about deforestation in Brazil based on satellite data indicated that up to 23% is triggered by cropland expansion and 66% by pasture expansion (Morton et al., 2006). By using the Landsat database from FAO, Gibbs et al. (2010) reavealed that between 1980 and 2000 about 55% of new agricultural land in the Pan-Tropics came from intact forests and about 30% from disturbed forests. Especially in South America, large-scale and enterprise-driven agriculture fuelled by rising consumer demand is a major cause (Parker et al., 2009). In contrast, in Central Africa, extraction of natural resources (e.g. timber) and in Pacific Asia pressure from commercial agricultural plantations are seen as the main driving forces behind the forest loss (Lambin et al., 2001). Although some recent sources have referred to a decreasing deforestation rate (Kauppi et al., 2006; FAO, 2010), the remaining rainforest worldwide is in severe danger due to increasing demand for food and other agricultural products (Gibbs et al., 2010).

Besides the general rise in agricultural demand, several studies point out that further trade liberalisation is and will be an important factor for deforestation activities. Barbier (2000) demonstrated this relationship with case studies from Ghana and Mexico. In Brazil, improved access to international markets has pushed soy and beef production causing a surge in deforestation (Fearnside, 2005; Nepstad et al., 2006). Based on satellite data DeFries et al. (2010) investigated that forest loss is largely driven by urban population growth and international exports of agricultural products. Other studies have used a global modelling approach to analyse future effects of trade liberalisation. Verburg et al. (2009) and Schmitz et al. (2012) have shown that tropical deforestation and global greenhouse gas emissions rise with increased trade liberalisation in the future. Similar studies have emphasized that liberalising trade leads only to small land use shifts in Europe but dramatic shifts in developing regions with negative implications for the environment (van Meijl et al., 2006; Eickhout et al., 2009).

To avoid further deforestation, researchers have investigated possible direct and indirect forest protection policies. Following Forner et al. (2006), interventions can be grouped along three basic lines: direct regulations, market instruments, and compensation payments. Direct regulations embrace mainly protected areas (PAs), which have a significant influence on the recent slowdown of deforestation in the Amazonian rainforest (Soares-Filho et al., 2010). As an alternative, the UNFCCC introduced the concept of committed forests, where measures for reducing deforestation are undertaken in designated areas (Forner et al., 2006). Market instruments include classic measures like taxes or subsidies but also the integration of avoided deforestation into a potential global carbon market (through emission trading). Especially, implications of the latter have been analysed extensively through the application of large-scale integrated land use models (Kindermann et al., 2008; Wise et al., 2009; Thomson et al., 2010). Finally, direct compensation payments, such as debt-for-nature swaps are used to protect forest and reduce the debt burden of developing countries at the same time (Shandra et al., 2011). Other more recent efforts, like Payments for Environmental Services (PES), could achieve progress towards forest conservation but under considerable transaction costs due to the involvement of many small-holder land owners (Wunder, 2007).

Previous studies have either focused on trade liberalisation or on forest-protection measures but none has looked on the important interplay. We here integrate both effects and consider explicitly the interaction between trade liberalisation and deforestation. We apply the economic land use model MAgPIE ("Model of Agricultural Production and its Impact on the Environment"), which takes global and regional interactions into account and simulates spatially explicit land use patterns. MAgPIE uses endogenously derived technological change and land expansion rates, which makes it unique in the field of land use modelling. Biophysical processes and inputs are considered through the link with the global vegetation-hydrology model LPJmL. The main goal of our study is to investigate consequences of different trade volume scenarios and forest protection policies on land use change, carbon emissions, net exports, and technological change rates over the coming five decades. As forest protection scenarios, we assume an expansion of protected areas, different carbon price scenarios and one case in which agricultural productivity in forest regions is increased due to higher Research & Development investments from developed countries. The latter is used to highlight the important interplay between land expansion and technological change (Lotze-Campen et al., 2010; Schmitz et al., 2010; Popp et al., 2012). We start by explaining the model framework with the implementation of trade and forest and by describing the applied scenarios. Following this, we present results of the analysis which are, finally, compared and discussed.

4.2 Methods

4.2.1 General model description

For the analysis we use the recursive dynamic optimization model MAgPIE ("Model of Agricultural Production and its Impact on the Environment"). In the following, we briefly present the main model features for this study. For further details we refer to extensive model documentations (Lotze-Campen et al., 2008, 2010; Popp et al., 2010, 2011a; Schmitz et al., 2012) and the mathematical description, which is attached as supplementary material.

Figure 4.1 presents a simplified flow chart of the inputs for MAgPIE. The model reflects three layers: global, regional (reflected by the ten world regions[2]) and cellular layers (based on 0.5 degree resolution). MAgPIE simulates time steps of 10 years (starting in 1995) and uses in each period the optimal land use pattern from the previous period as a starting point. Required calories in the demand categories are derived through a cross-country regression based on a medium population scenario (United Nations, 2011) and a medium income growth scenario (projections based on Heston et al. (2011)). International trade determines how many calories are produced domestically and how many are imported. In MAgPIE, trade can be either fixed, if it is allocated according to historic self-sufficiency rates (1995 values from FAOSTAT (2010)), or liberalized, which means that regions with comparative advantages produce more at the expense of less competitive regions. The share of the two options is determined by the trade balance reduction factor $p_t b$ (see Figure 4.1). More details on the trade implementation are described in Schmitz et al. (2012). The resulting calories are produced by 16 cropping and 5 livestock activities[3] in the particular regions.

Further inputs of MAgPIE are socio-economic data, mainly costs, which define the cost minimization objective function. In the baseline version of the model four categories of costs arise: 1) Production costs are taken from GTAP (Narayanan and Walmsley, 2008) and contain factor costs for labour, capital, and intermediate inputs. 2) Technological change costs are based on investments in agricultural Research & Development as well as infrastructure investments (Schmitz et al., 2010). They arise exponentially with the state of agricultural development of a region (Dietrich et al., 2012). 3) Land expansion involves costs for preparation of new land and basic infrastructure investments (Krause et al., 2012). Regarding the conversion of intact and frontier forests (IFF) we base our cost parameterisation on reference values from case studies. Merry et al. (2002) analysed forest transition in Latin America with a case study of Bolivia and calculated conversion costs of 600 to 700 US$/ha. Similar costs accrue in Indonesia with 550 US$/ha for converting rainforest to cropland (Simorangkir, 2007). Another

[2] AFR = Sub-Sahara Africa, CPA = Centrally Planned Asia (incl. China), EUR = Europe (incl. Turkey), FSU = Former Soviet Union, LAM = Latin America, MEA = Middle East and North Africa, NAM = North America, PAO = Pacific OECD (Australia, Japan and New Zealand), PAS = Pacific Asia, SAS = South Asia (incl. India)

[3] Cropping Activities: temperate cereals (tece), maize, tropical cereals (trce), rice, soybean, rapeseed, groundnut, sunflower, oil palm, pulses, potato, cassava, sugar beet, sugar cane, cotton, others; Livestock Activities: ruminant meat, pig meat, poultry meat, egg, milk

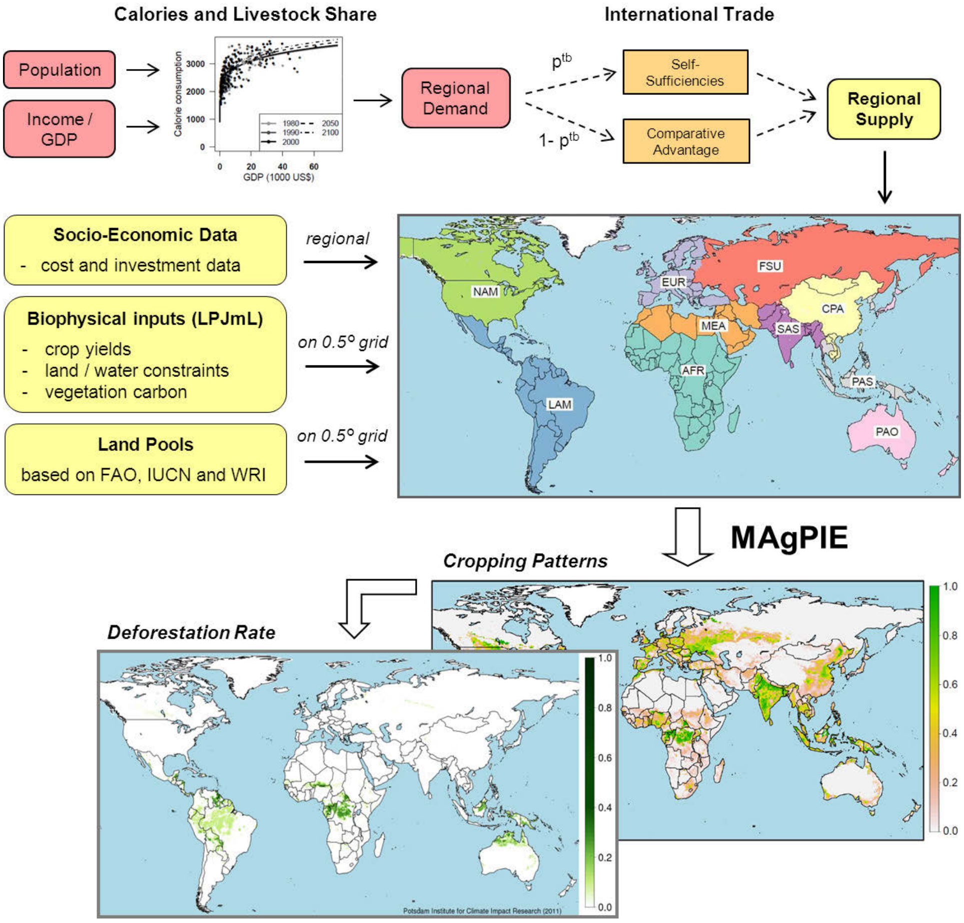

Figure 4.1: Simplified MAgPIE flow chart of key processes highlighted in this study (demand and trade implementation, land pools and spatially explicit land use change). With exogenous data about population and GDP development, we calculate regional demand and the livestock share. The former is then translated to regional supply depending on the international trade scenario. Further inputs for MAgPIE are socio-economic data like production costs, biophysical inputs from LPJmL and land type data based on various sources (FAO, IUCN and WRI). After optimization of MAgPIE, possible outputs are cropping patterns of different crops or maps with deforestation rates.

case study from Latvia, however, reveals with 1,500 US$/ha considerably higher costs (Lazdins et al., 2009). In developed countries this value (based on marginal access costs) increases even further up to 7,500 US$/ha (Sohngen et al., 2009). The large variation in costs is due to a number of criteria like topography, forest type, soil conditions, applied technology, and the governmental system. As a base value we assume 1,000 US$/ha for tropical land conversion. We applied a sensitivity analysis of this parameter by varying it in 200 US$ steps from 200 US$ to 1,800 US$ (see Figure 4.9). 4) Intraregional transport costs for every commodity unit reflect the distance to intraregional markets and the quality of the infrastructure. Data for transport costs are derived from GTAP (Narayanan and Walmsley, 2008) and travel time to the nearest city is reflected by a 30 arc-second resolution data set (Nelson, 2008).

For the represenation of biophysical processes, MAgPIE is linked to the global biophysical vegetation-hydrology model LPJmL (Bondeau et al., 2007). LPJmL endogenously models the dynamic processes linking climate and soil conditions, water availability and plant growth, and takes the impacts of CO_2, temperature and radiation on yield directly into account. The link to MAgPIE is generated via rainfed and irrigated yields for different crops, rainfed and irrigated land use fractions (Fader et al., 2010), water inputs, like irrigation requirements and water availability (Rost et al., 2008) and the carbon content of the various vegetation types. These outputs from LPJmL are used in a 0.5 degree resolution in MAgPIE. The same resolution is used for the determination of land types per grid cell. The different land pools are taken from a consistent land use database developed by Krause et al. (2009) which is based on Erb et al. (2007) and integrates crop suitability indicators (van Velthuizen et al., 2007), intact and frontier forest types (Bryant et al., 1997; Potapov et al., 2008), and protected areas (UNEP, 2006). Intact and frontier forests can also be denoted as undisturbed natural forests. Together with other natural vegetation not defined as grazing land or forest (around 122 million ha), it constitutes the land pool that is made available for cropland expansion (around 734 million ha). The remaining land pools, like pasture and managed forests, are not regarded for cropland expansion. When land use change occurs and land is converted to a different type (e.g. forest to cropland), MAgPIE accounts for carbon emissions by taking the differences in LPJmL-derived carbon stocks between the two land pools. The used LPJmL model version is able to capture changes in above and belowground vegetation carbon (see Figure 4.2) but not in soil carbon. Related carbon emissions are reported as CO_2-equivalent emissions after each time step.

4.2.2 Scenario design

The aim of this study is to investigate interactions between international trade policy and forest protection measures (Table 4.1) and their consequences on tropical deforestation patterns.

Concerning trade policy, our analysis largely follows the policy scenario of the predecessor study (Schmitz et al., 2012), except that trade liberalisation starts in 2015 (instead of 2005). Hence, our reference case keeps the trade patterns fixed over time,

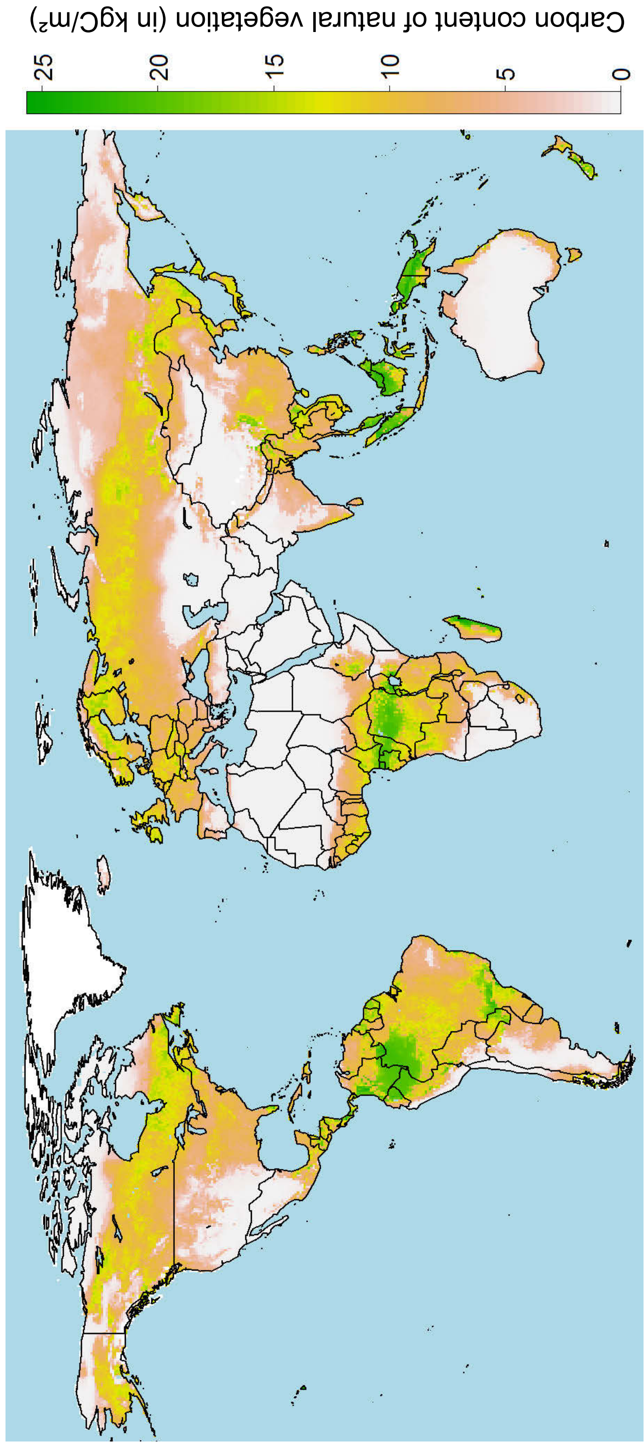

Figure 4.2: Grid-cell specific carbon content (0.5 degree) of natural vegetation (in kgC/m^2) from LPJmL (average from 1990-1999) used in MAgPIE

Table 4.1: Scenario Definition

Policies	**Trade policy**	**Forest policy**		
Scale	*global*	*AFR*	*LAM*	*PAS*
Reference Scenario [*reference*]	constant	- basic forest protection -		
Trade Scenarios:				
(a) no forest policy [*nopol*]	liberalisation	- basic forest protection -		
(b) Increasing Forest Protection over time [*time*]	liberalisation	until 2040	until 2030	until 2030
(c) Low CO_2-Price [*lowprice*]	liberalisation	- low CO_2-Price -		
(d) CO_2-Price to achieve 550 ppm [*550ppm*]	liberalisation	- high CO_2-Price -		
(e) Additional investment in TC [*TC*]	liberalisation	- 1% TC p.a. -		

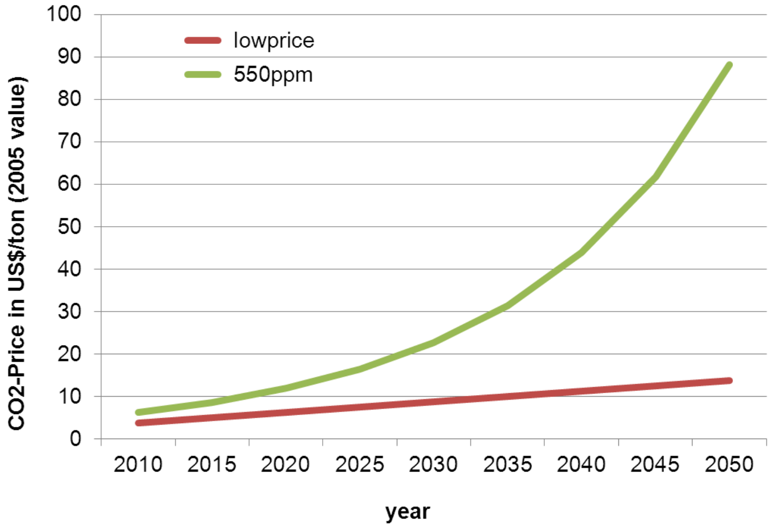

Figure 4.3: Modelled CO_2-Price (in US$/ton) for the *lowprice* and *550ppm* scenario until 2050

whereas the trade scenarios assume further progress in the Doha Development Round [4], leading to liberalisation efforts comparable to situations in the 1980s and 1990s, when large global liberalisation efforts were undertaken. Based on Dollar and Kraay (2004) and Conforti and Salvatici (2004), we assume that trade barriers are continuously reduced by 10% each decade. The trade policy is the same in all five trade scenarios, but the scenarios differ according to their forest policy (Table 4.1). Whereas the scenario *nopol* assumes no forest protection measures in order to highlight the differences of the trade effect compared to the reference case, the other four scenarios assume different global and regional policy measures to reduce deforestation.

As a first scenario, we introduce policies to restrict deforestation and to implement protected areas (PAs). Based on Soares-Filho et al. (2006) we consider a defined share of intact and frontier forest as protected and increase this share over time (*time* scenario). For the three main tropical IFF regions we assume a different time span (2040 in AFR and 2030 in LAM and PAS) until full forest protection is achieved depending on awareness level and governmental structures (Table 4.2).

As a further scenario set-up, we introduce a CO_2 price as climate mitigation policy, which will be paid for avoided deforestation and increases opportunity costs of land conversion. In contrast to other approaches, which use constant carbon prices over time (e.g. Kindermann et al. (2008)), our price assumption rises over time. We differentiate two cases. First, we reflect a non-market approach by applying a low price scenario (*lowprice*), in which the price per ton of CO_2 starts at 5 US$ and rises continuously

[4] The Doha Development Round it the latest round of trade negotiations of the World Trade Organisation (WTO). It was launced in 2011 with the aim of improving the access to global markets. For more information on the stage and agenda of the Doha Round, see Martin and Mattoo (2011).

Table 4.2: Forest protection rate in the past (2000-2010) and assumed rates for the future (2010-2050) in the trade scenario *time*

Scenario	**Region**	**2000-10**	**2010-20**	**2020-30**	**2030-40**	**2040-50**
Basic Protection	*AFR*	8%	8%	8%	8%	8%
(observed)	*LAM*	25%	25%	25%	25%	25%
	PAS	12%	12%	12%	12%	12%
Protection over time	*AFR*	8%	31%	54%	77%	100%
(assumed)	*LAM*	25%	50%	75%	100%	100%
	PAS	12%	41%	70%	100%	100%

to 12.5 US$ (Figure 4.3). The assumption behind this is that avoided deforestation is not included in a potential global carbon market or emission trading scheme, but that a non-market-based price will be paid by the global community to reward forest protection (based on Angelsen (2008)). In a second CO_2-price scenario, called *550ppm*, we consider the other case, in which avoided deforestation is included in a potential global carbon market. The resulting CO_2-price is based on modelling results from the ReMIND model for the Energy Modelling Forum (EMF-24) (Luderer et al., 2012), which assumes a maximum concentration of greenhouse gas emissions of 550 ppm (Figure 4.3). Finally, the last scenario assumes that the three forest regions, Latin America (LAM), Sub-Sahara Africa (AFR) and Pacific Asia (PAS) receive financial means to increase their yields by 1% per year. This kind of exogenous technological change (TC) is a special case since no direct intervention of forest protection is assumed and only indirect effects on the forest area will be obtained. The hypothesis behind this scenario is that higher investments in TC can reduce the rate of forest destruction without any forest protection.

4.3 Results

4.3.1 Deforestation and carbon emissions

Table 4.3 provides an overview about the potential area of IFF in the three forest regions in 2050 as well as the change between 2010 and 2050 under the different scenarios. The concentration of tropical intact and frontier forest (IFF) in Latin America ($\sim$ 80%) is also reflected in the deforestation patterns, as the region sees the highest forest loss in all scenarios. Since a much smaller share of tropical IFF is located in Central Africa ($\sim$ 10%) and South-East Asia ($\sim$ 9%), deforestation is absolutely quite small, but percental changes in IFF are much higher than in LAM (in Central Africa up to 99% depending on the scenario).

In Latin America around 140 million ha of IFF is deforested between 2010 and 2050 in the reference case, leading to 60 Gt CO_2 emissions. With additional trade liberalisation this value grows to 180 million ha and about 85 Gt CO_2 emissions. The forest protection scenario (*time*) and the two price scenarios (*lowprice* and *550ppm*) lead to lower deforestation rates than in the reference case and to almost no emissions after 2040 (Figure 4.4). With exogenous TC, additional CO_2 emissions can be reduced to a similar level like in the reference case (60 Gt CO_2). Most effective is the integration of avoided deforestation in a potential carbon market [*550ppm* scenario), leading to a total IFF loss of only 20.4 million ha and corresponding emissions of 5.5 Gt CO_2. In the *lowprice* scenario deforestation is reduced to 69 million ha and with full forest protection until 2030 around 92 million ha will still be cleared prior to 2030.

For the Central African rainforest the picture looks different. Almost all IFF will be gone under the $reference$, the *nopol* and the TC scenarios (around 63 million ha). This leads to relatively more CO_2 emissions (40 Gt), since the average carbon content in AFR is higher than in the deforested area in LAM. Full forest protection until 2040 saves 9.2 million ha of IFF, the *lowprice* scenario saves around 35 million ha and the

Table 4.3: Intact and Frontier Forest (IFF) in 2050, deforestation area (2010-2050), associated CO_2 emissions and the average carbon content of deforested area in the different scenarios

Region	**Result**	**Unit**	**reference**	**nopol**	**time**	**lowprice**	**550ppm**	**TC**
Latin America (LAM)	IFF in 2050	10^6 ha	339.5	299.7	388.5	411.1	459.6	343.3
	Deforestation (2010-50)	10^6 ha	140.5	180.3	91.5	68.9	20.4	136.7
	CO_2 emissions (2010-50)	Gt CO_2	60.0	84.5	42.9	27.3	5.5	58.3
	Average carbon content	kgC/m^2	11.7	12.8	12.8	10.8	7.4	11.6
Sub-Sahara Africa (AFR)	IFF in 2050	10^6 ha	0.7	0.9	9.2	34.5	63.6	1.1
	Deforestation (2010-50)	10^6 ha	63.7	63.5	55.2	29.9	0.8	63.3
	CO_2 emissions (2010-50)	Gt CO_2	40.8	40.5	36.2	17.0	0.5	38.8
	Average carbon content	kgC/m^2	17.5	17.4	17.9	15.5	15.4	16.7
Pacific Asia (PAS)	IFF in 2050	10^6 ha	31.2	35.0	50.3	47.1	45.2	49.4
	Deforestation (2010-50)	10^6 ha	24.3	20.5	5.2	8.4	10.3	6.1
	CO_2 emissions (2010-50)	Gt CO_2	10.9	9.9	2.6	0.9	2.1	2.8
	Average carbon content	kgC/m^2	12.2	13.2	13.6	2.9	5.6	12.5

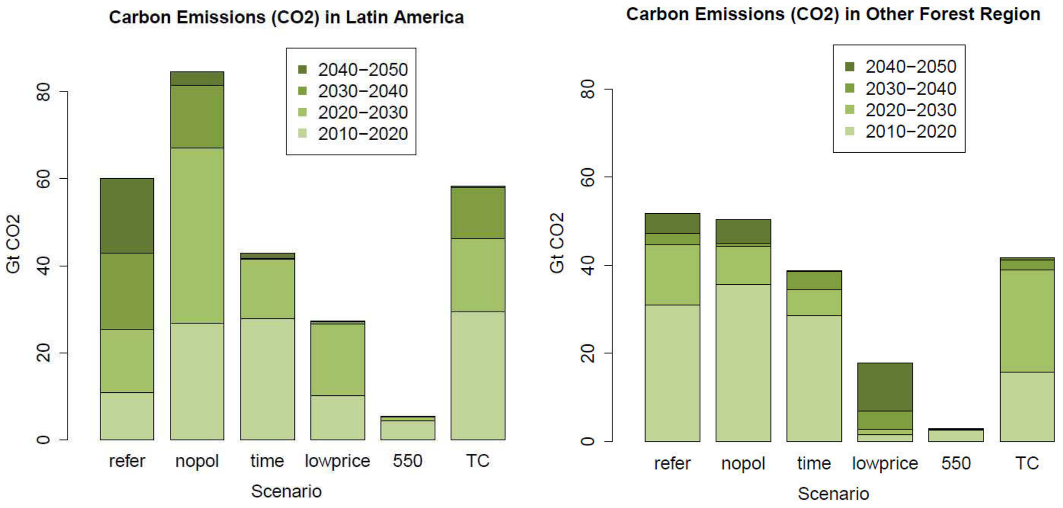

Figure 4.4: CO_2 Emissions (in Gt) from tropical deforestation over time and for the two forest regions (LAM and OFR)

550ppm scenario saves almost the whole IFF (64 million ha). In Pacific Asia, deforested area decreases under trade liberalisation. Additionally, in contrast to the other regions, the *time* and *TC* scenarios are most effective by conserving around 50 million ha of the original 55.5 million. Additionally, the lower CO_2-price saves 2 million ha more than the higher price scenario (*550ppm*).

The average carbon content per deforested hectare in all scenarios is highest in Central Africa (Table 4.3), where the northern part of the rainforest has the highest carbon intensities (see Figure 4.2). In South America average carbon intensity is lower, since mostly border cells with a lower carbon content are affected by deforestation (see Figure 4.5). In general, the model chooses the cells for deforestation according to the costs and the potential agricultural yield. In the CO_2-price scenarios (*lowprice* and *550ppm*), however, the carbon content is an additional influencing factor. In these scenarios, we observe a substantial reduction in the average carbon content since the model has an explicit incentive to minimize carbon release by choosing low carbon cells for land conversion.

For presentation purposes we have aggregated the model results into four regions. Latin America is kept separately due to its importance for IFF and the agricultural sector. Sub-Sahara Africa and Pacific Asia are grouped to the category "Other-tropical-Forest Regions" (OFR). For net export and technological change rates, the remaining regions are grouped to Non-tropical-Forest Developing Countries (NFDC) (mainly China, India, Russia, and the Middle East) and OECD countries. The pace of deforestation varies substantially between scenarios (Figure 4.4). Forest clearance in LAM is much faster under the nopol scenario than under the reference scenario (drawing level with the 2030 baseline values in 2020 and exceeding the 2050 baseline in 2030). Including a

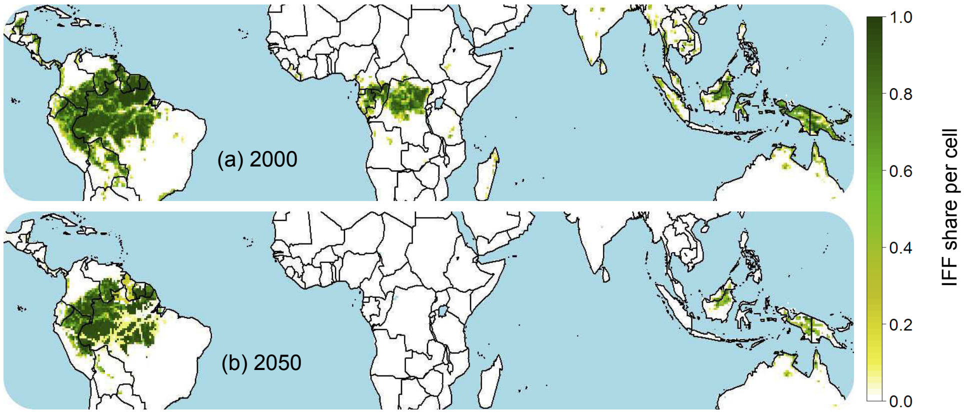

Figure 4.5: Share of tropical intact and frontier forest per grid cell in the reference case in the years 2000 and 2050

low CO_2-price reduces emissions in LAM until 2050 to a level compared to the *nopol* scenario in 2020. In OFR, we obtain that in some scenarios (reference, *nopol*, *lowprice*) deforestation is higher in the last time step than in the penultimate time step. In the other scenarios almost no deforestation takes place after 2040 due to full protection (*time*), high CO_2 prices (*550ppm*) or high agricultural productivity (TC).

In the following, we present grid-specific maps, which support the understanding of local dynamics. Figure 4.5a presents the tropical intact and frontier forest (IFF) in the year 2000. The tropical IFF forest is mainly located in Amazonia, Central Africa (mainly DR Congo, Cameroon, Gabon and Congo) and South-East Asia (mainly Malaysia, Indonesia, the Philippines and Papua New Guinea). Compared to the state in 2000, Figure 4.5b highlights the potential area of IFF in 2050 for the reference case. The Amazonia rainforest is considerably reduced especially at the borders in the South and West, but also within the forest, where infrastructure exists. The situation in Central Africa is even more intense, since in the reference case all IFF area would be cleared. In Pacific Asia forest area is reduced significantly in some locations, up to a complete loss of IFF.

To analyze the importance of trade liberalization and forest protection measures in a spatially-explict way, we investigate the scenarios' differences to the baseline setting in 2050 with difference maps (Figure 4.6). Positive values indicate a higher share of IFF in the scenarios and a negative value indicates further deforestation. The effects of trade liberalization on deforestation rates are shown in Figure 4.6a ($reference$ in 2050 minus *nopol* in 2050). In Latin America, the Northern part of Amazonia and some borderland in the west are most negatively affected by trade liberalisation. Additionally, the interior close to existing infrastructure faces slight increases in deforestation. In Africa nothing changes as the whole forest would be gone in both scenarios, whereas Pacific Asia has lower and North Australia higher deforestation rates. Analyzing the effects of forest protection measures, we show that deforestation LAM is very sensitive to forest protection. If parts of the rainforest are protected with an increasing rate (Figure 4.6b),

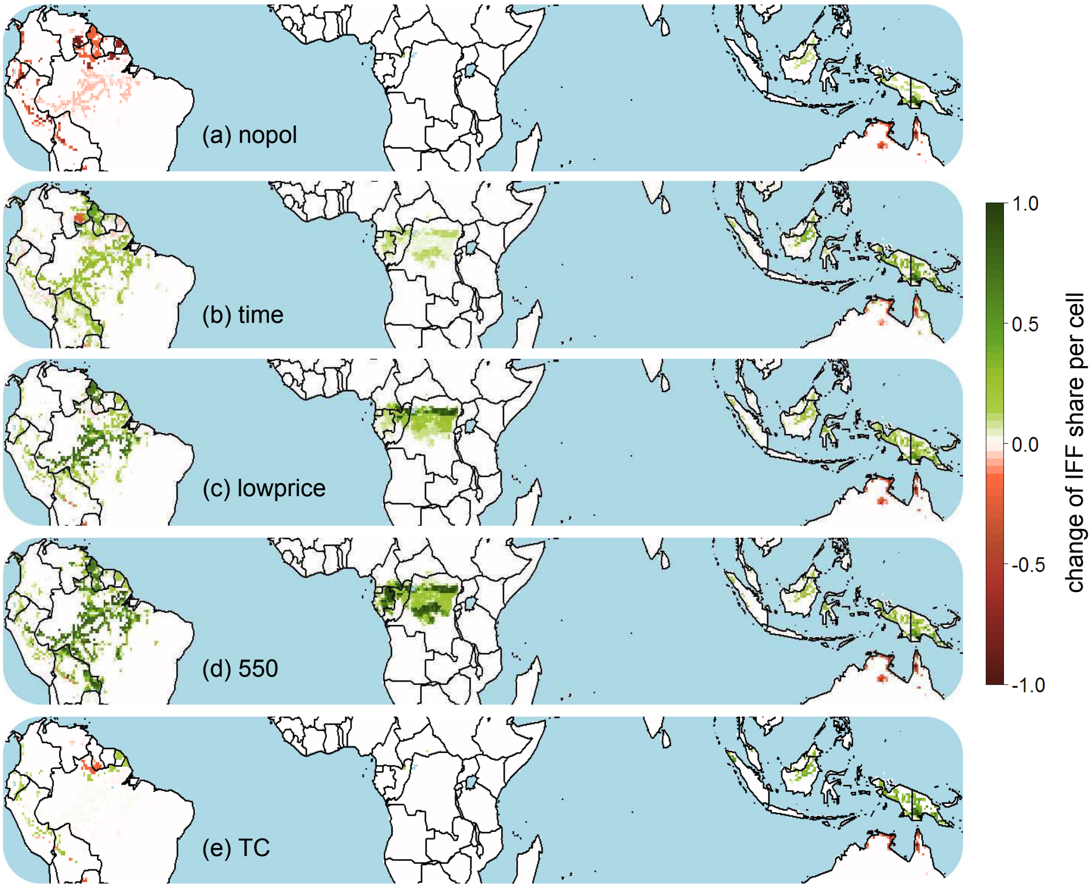

Figure 4.6: Change of intact and frontier forest share per grid cell in the five trade scenarios compared to the reference case in 2050 (Red cells diplay additional deforestation, green cells display less deforestation)

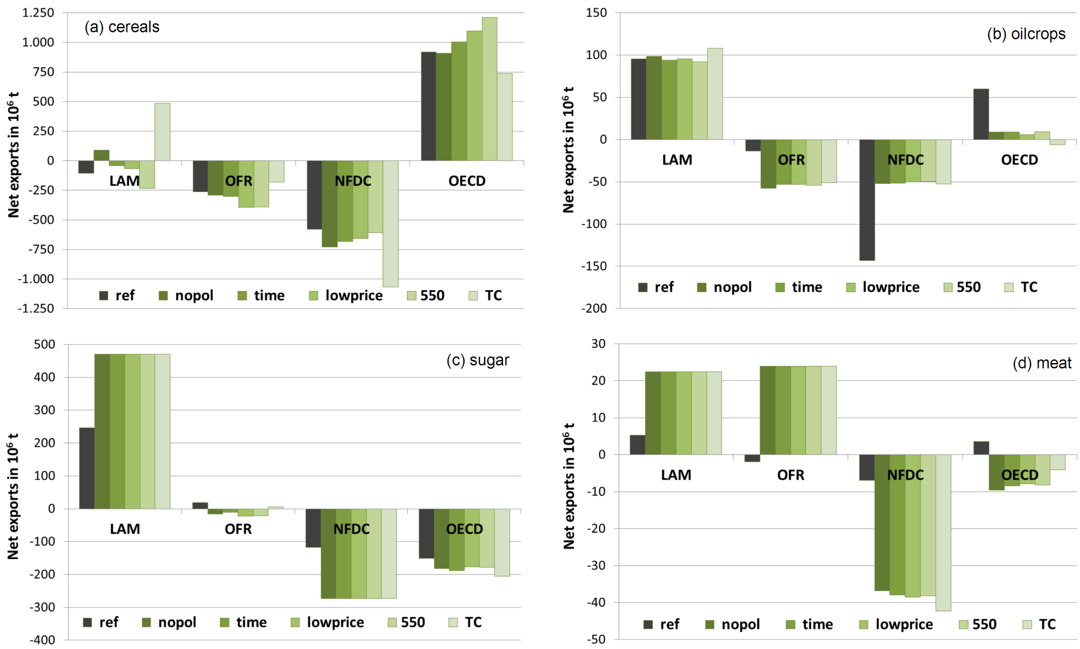

Figure 4.7: Aggregated net exports (from 2010-2050) for selected traded commodities (cereals, oilcrops, sugar and meat) in Latin America (LAM), Other Forest Regions (OFR), Non-tropical-Forest Developing Countries (NFDC) and OECD countries

it mostly helps interior areas of the forest. Only some cells in the north of the forest are still deforested but to a lower extent than without protection policy. Both CO_2-price scenarios lead to much lower deforestation rates in the interior of the forest. In the *550ppm* scenario this is most effective in the south (Figure 4.6d). Finally, in the *TC* scenario almost no differences can be detected compared to the reference case with respect to South America, except for some boarder cells in the north and the west. In Africa, the CO_2-price scenarios have the biggest effect on deforestation, protecting the northern part and in the *550ppm* scenario also the southern and western part. The expansion of protected areas (*time* scenario) has only small effects on deforestation patterns and investments in agricultural productivity (*TC* scenario) have no effects on deforestation as the whole forest is still cleared for agriculture. In Pacific Asia, all forest protection measures have positive effects with highest forest savings in Papua New Guinea.

4.3.2 Net export and technological change rates

The analysis of net export rates indicates regions with comparative advantages in agricultural production. Figure 4.7 illustrates net export rates for cereals, oilcrops, sugar, and meat in the reference case and the trade scenarios.

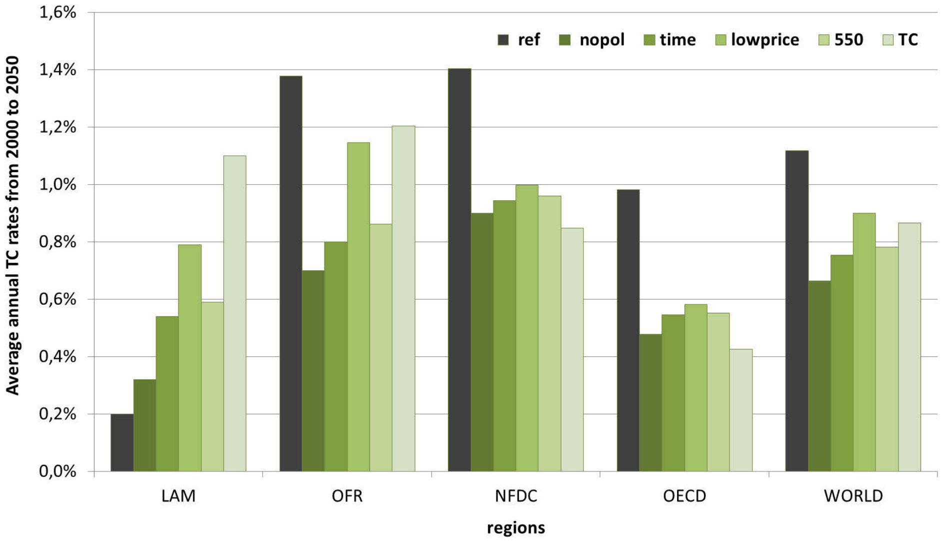

Figure 4.8: Average annual technological change rates in Latin America (LAM), Other Forest Regions (OFR), Non-tropical-Forest Developing Countries (NFDC) and OECD countries

In general, under trade liberalisation, Latin America exports more of every commodity compared to the reference scenario. In case of cereals, LAM turns from a net importer to a net exporter. Under forest protection, LAM becomes a net importer again whereas the *TC* scenario generates highest cereal net exports. Other commodities are less (oilcrops) or not at all (sugar, meat) affected by various forest protection policies and remain on a high export level. Trade liberalisation allows Non-tropical-Forest Developing Countries (NFDC) to reduce their imports in oilcrops at the expense of OECD countries, which face a drop in export levels. The rise in sugar exports in LAM leads to additional imports in NFDC and OECD countries. Concerning meat, the overall extent of trade is rather low in 2050. Regions with tropical IFF increase their exports in livestock, whereas NFDC increase imports and OECD countries turn from exporters to importers.

Technological change (TC) rates are endogenously derived by MAgPIE, indicating the need for investments in the technological development of the agricultural sector per region. For LAM, TC rates are rather low in the reference case but grow with further trade liberalisation (Figure 4.8). Forest protection further increases the need for TC, with highest rates in the *lowprice* and *TC* scenario. In all other regions, TC rates decrease with trade liberalisation compared to the reference case. In OFR, highest TC rates among the trade scenarios are achieved with the *lowprice* and *TC* scenarios. NFDC and OECD countries achieve highest TC rates among the trade scenarios in the *lowprice* scenario. On an aggregated global level, highest TC rates are needed in the reference case and lowest in the *nopol* scenario.

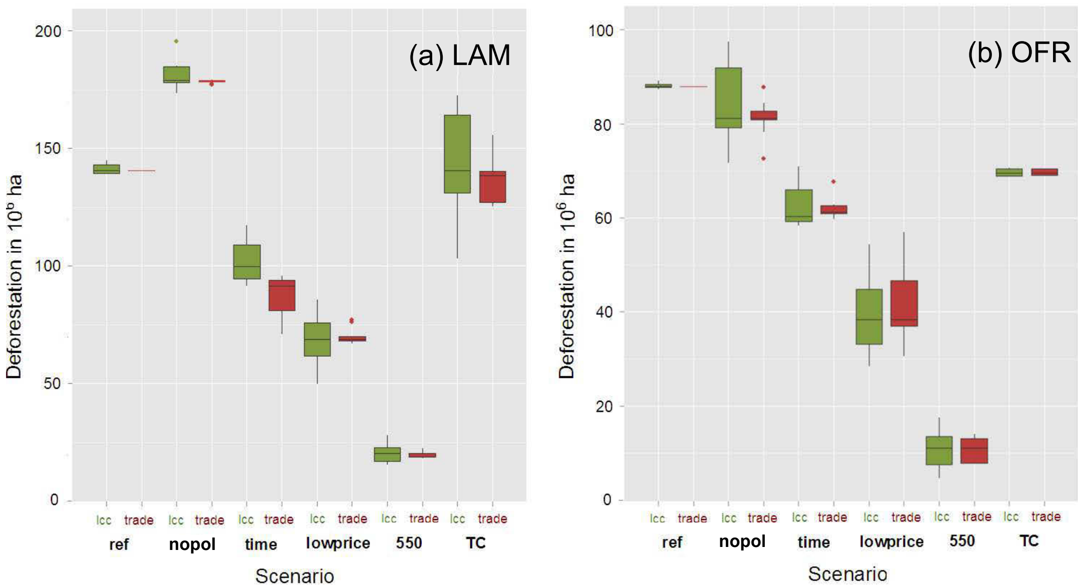

Figure 4.9: Sensitivity of intact and frontier forest (IFF) area in LAM (Latin America) and OFR (Other Forest Regions) in 2050. For the analysis, land conversion costs (*lcc*) are varied in 200 US$/ha - steps from 200 US$/ha to 1,800 US$/ha (green boxplots) and the trade balance reduction (*trade*) is varied in 2.5% steps (up to 10%) around the current setting (red boxplots). The boxplots display minimum, lower quartile, median, upper quartile and maximum values.

4.3.3 Sensitivity analysis

Our model results depend largely on exogenous parameters. In order to verify the results we regularly perform sensitivity tests with the crucial parameters. For this study we have chosen land conversion costs (lcc) and the trade balance reduction factor, which triggers the amount of trade liberalisation. In the first case we vary lcc from 200 US$/ha to 1800$/ha in 200 US$/ha steps in each scenario, which amounts to 54 model runs. The same amount of model runs is required for the second sensitivity test, in which we vary the trade balance reduction factor by 2.5%, 5%, 7.5% and 10% below and above current values in each time step.

Resulting boxplots display the variation (minimum, lower quartile, median, upper quartile and maximum) in deforestation area of land conversion costs in green and the trade balance reduction in red for each scenario and the forest regions (LAM and OFR) (Figure 4.9). We obtain a quite heterogeneous picture with the general trend that the model outcome appears to be much more sensitive towards variations in land conversion costs than in trade liberalisation. However, in most cases the rank order between scenarios is not affected, except two cases: The *TC* scenario in LAM and the *nopol* scenario in ORF appear to be either higher or lower in deforestation than the reference case depending on the chosen land conversion costs.

4.4 Discussion

During preindustrial history, demand for agricultural land, fuelled by population growth, has been the main driver for deforestation in temperate zones (Simmons, 1987). After the industrial revolution the situation started to change and rising wealth of industrialized countries initiated a domestic forest transition[5] (Meyfroidt and Lambin, 2011). However, increased globalisation and growing demand in developed countries has shifted parts of the production to land-rich developing countries leading to tropical deforestation (Lambin et al., 2001). This relation, also referred to as virtual trade of land (Würtenberger et al., 2006; von Witzke and Noleppa, 2010), is triggered by the costs of trade (like tariff, transport and information costs), which have been substantially reduced during the past century (Feenstra, 2008; Jacks et al., 2008). Since it is likely that this trend will continue (Josling, 2010), considerable damages for the local environment and society as well as the global climate system resulting from deforestation can be expected. Questions arise how future growth in trade affects deforestation rates and how different forest protection policies might influence the interplay between land expansion and trade competitiveness.

With the spatially explicit land use model MAgPIE we analyse effects of trade liberalisation and different forest protection policies. Compared to other global land use models it has the advantage that technological change and land expansion are implemented in an endogenous and competitive way. Associated investment costs are optimized together with production and transport costs on a global level. Biophysical inputs are derived from the process-driven vegetation-hydrology model LPJmL. In this study we do not explicitely consider future scenarios of bioenergy demand, since it has been done in separate studies with the ReMIND-MAgPIE model system (Popp et al., 2011a, 2012). As shown by them and others (Gibbs et al., 2008), bioenergy is only carbon-saving, if additional agricultural production does not come at the expense of forest land or alternatively, is achieved by agricultural productivity gains.

Our simulation results for 2000 to 2010 are in good agreement with observation data (FAO, 2011b). For instance, in the case of Latin America, we simulate an average annual deforestation rate of 3 million ha of intact and frontier forest (IFF) compared to 4.25 million ha observed by FAO in this period. However, since FAO considers the whole unmanaged forest, the deforested IFF area in FAO statistics should be lower and much closer to our value. Nepstad et al. (2009) report an annual value of around 2 million ha (1996-2005), only for the Brazilian Amazon. In contrast, in Central Africa (4.5 vs. 3.4) our values are moderately higher and in Pacific Asia (2.7 vs 0.9) significantly higher than FAO observations. The large gap in Pacific Asia can be partly explained by recent reforestation efforts in this region (Lamb, 2011), which are considered in FAO statistics but are not relevant for our definition of IFF.

[5]Forest transition is defined as a period when regions shift from net deforestation to net reforestation.

Overall, our results show that in the main forest regions, Latin America, Sub-Sahara Africa, and Pacific Asia, cropland area would significantly increase over time under constant trade and forest protection. With growing trade liberalisation the most prominent region in terms of IFF area, Latin America, would clear additional 40 million ha forest area, leading to 25 Gt additional CO_2 emissions by 2050. At the same time due to its comparative advantage, Latin America is the only region which requires higher technological change (TC) rates than in the reference case and expands its exports in every of the four major traded commodities (cereals, oilcrops, sugar, and meat). In contrast, Sub-Sahara Africa reduces its production level due to trade liberalisation. However, this decrease has no influence on the deforestation level and is purely triggered by lower investments in technological change. Countries in Pacific Asia decrease their deforestation rate under liberalisation compared to the reference case. The main reason is that comparative advantages in most agricultural commodities in those countries are low, which lead to further imports under liberalisation. However, the pace of deforestation there still increases with liberalisation, leading to higher rates until 2020. Land-scarce regions like the Middle East, North Africa, and South Asia are projected to see the highest growth in imports. With increasing liberalisation there is less pressure to increase productivity in these regions, resulting in significantly lower investments in technological advances.

Reducing emissions from land use change requires intervention to protect forests. We combined trade scenarios with different forest protection measures, divided into direct regulations, market instruments, and compensation payments. In general, forest protection leads to higher investments in TC, especially in Latin America. Except for some slight reductions, net export rates stay constant due to higher agricultural productivity. Hence, forest regions do not lose their competitive advantage as a consequence of forest protection.

As a direct regulation we increased protected areas (PAs) over time. Soares-Filho et al. (2010) tried to quantify the impact of PAs in the Amazonian rainforest and concluded that 37% of the recent decline in deforestation was due to new PAs and 44% due to lower agricultural activity. In another study they estimated a reduction in deforestation of around 100 million ha by comparing a business as usual case with a strict governance scenario (involving an expansion of PAs and other legal protection enforcements) (Soares-Filho et al., 2006). Our continuously increasing rate of PAs in Latin America (*time* scenario), follows their governance scenario as far as possible and achieves savings of almost 90 million ha compared to a scenario without any further forest protection (*nopol*). Nepstad et al. (2009) even discussed the possibility of ending deforestation by 2020 (which is confirmed by our *550ppm* scenario), based on the assumed continuation and extension of recent efforts, like expansion of PAs, externally-financed funds and regulation efforts by the agri-business sector. However, if not monitored or applied globally, protecting forests at one place can lead to displacement of land use to other regions (Soares-Filho et al., 2010; Meyfroidt et al., 2010) and resulting carbon leakage (Wunder, 2008). Although we have not directly analysed this mechanism, we observe some non-continuous effects between different time steps and scenarios. For instance, in ORF between 2030 and 2040 deforestation is higher in the scenarios *time* and *lowprice* compared to the *nopol* scenario, whereas it is the other way round for LAM. Since agricultural area is not allowed to expand into IFF in LAM and PAS in this time step, agricultural area in Central Africa expands at the expense of IFF area. The establishment of protected areas should, therefore, be an international effort in order to avoid leakage effects and to support the political will in target countries (Soares-Filho et al., 2006).

As a representative policy for market instruments, we included a CO_2-price as a climate mitigation policy for avoided deforestation. With a price sufficiently high to reach the 550ppm concentration target, total emissions related to deforestation are below 10 Gt CO_2 by 2050. This rather sensitive behaviour is in line with other studies. The MiniCAM model is even more sensitive towards a CO_2-price by generating no land use related carbon emissions in a *550ppm* scenario (Wise et al., 2009). Its successor, the GCAM model, calculates deforestation levels under a 526ppm scenario amounting to around 30 Gt emissions between 2020 and 2050 (Thomson et al., 2010). Finally, the study by Kindermann et al. (2008) provides a comparison of three different models, GTM, DIMA and GCOMAP, by calculating marginal abatement cost curves. They show that with assumed constant carbon prices, deforestation in Latin America is fully avoided in 2020 with a CO_2 price between 30 and 40 US$/ton. In our study, this is already achieved with prices of 12 to 20 US$/ton. With regards to climate mitigation, the inclusion of CO_2 prices has the advantage over other measures that the carbon intensity per unit of land is explicitely considered. As a consequence carbon-rich vegetation is valued higher and land expansion moves to places where forests and other natural vegetation contain relatively less carbon.

Lastly, we applied a scenario of indirect forest protection in order to investigate the effect of additional growth in agricultural productivity on deforestation (*TC* scenario). Results suggest that investments in technological change could potentially reduce the pressure on tropical forests. However, it has to be noted that an additional yield growth of 1% per year requires huge investments in the agricultural sector (Schmitz et al., 2010) and that this yield increase would not be sufficient to prevent deforestation completely. As shown by others as well, additional and complementary measures are needed (Wise et al., 2009; Thomson et al., 2010). In this context, Angelsen (2010) points out that local yield increases may encourage local deforestation and that, therefore, agriculture in low-forest areas should be supported instead of agriculture close to the forest frontier.

4.5 Conclusion

From our analysis we draw several conclusions. First, more trade liberalisation leads to a net increase of deforestation driven by the strong growth in agricultural exports, mainly in Latin America. This result confirms that deforestation in the tropics is often fuelled by accelerating international demand. Therefore, global liberalisation efforts, e.g. by the WTO, should not be undertaken without considering global forest protection measures. Meyfroidt et al. (2010) suggested a similar strategy, pointing out the importance of integrating agricultural trade in international deforestation policies. Under the UNFCCC framework, REDD+ (Reducing Emissions from Deforestation and forest Degradation), a mechanism that aims to reduce carbon emissions from deforestation by providing financial incentives, is a viable and promising attempt (Ebeling and Yasue, 2008), if leakage into non-target countries is prevented (Miles and Kapos, 2008).

Second, policies to protect forest area do not necessary lead to losses in trade competitiveness, since the reduced land availability is in most cases compensated by higher technological change rates. This contradicts often expressed concerns that policies to protect forests reduce economic growth or international competitiveness (Banerjee et al., 2009).

Third, the integration of avoided deforestation into a global emission trading scheme seems to be most effective since it has the strongest effect and also makes sure that leakage effects are largely avoided. Although the implementation is more challenging than initially thought (Angelsen, 2008), some valuable proposals for integrating the forest sector into an international climate agreement have been made (Mollicone et al., 2007; Huettner et al., 2009). Alternatively, non-market solutions like Payments for Environmental Services (PES) have been proposed, since the implementation is likely to be less complicated and, therefore, faster (Angelsen, 2008). However, Wunder (2007) emphasizes that PES schemes suffer from high transaction costs and face challenges to clearly fulfill the additionality criteria. As a consequence of the drawbacks, partial market integration concepts, which aim for a separate market for REDD units, entered the discussion (CCAP, 2007; Greenpeace, 2007). The main advantage is that a major source of carbon emissions would be included in the market mechanisms for mitigation and developing countries with significant forest area would have the means to take on real, sectoral commitments and reduce emissions on a voluntary basis.

Fourth, developed countries drive tropical deforestation due to their agricultural demand and should be aware of their responsibility regarding virtual trade of land. One possibility would be to introduce certification programs together with their exporting counterparts (Meyfroidt et al., 2010). Furthermore, financial support of forest protection measures (e.g. the Amazon fund supported by Norway (Tollefson, 2009)) or alternatively investments in agricultural productivity are viable options.

5 Blue water scarcity and the economic impacts of future agricultural trade and demand[1]

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Abstract

An increasing demand for agricultural goods will affect the pressure on global water resources over the coming decades. In order to quantify these effects we have developed a new agro-economic water scarcity indicator considering explicitly economic forces in the agricultural system. The indicator is based on the water shadow price generated by an economic land use model linked to a global vegetation-hydrology model. Irrigation efficiency is implemented as a dynamic input depending on the level of economic development. With a spatially explicit representation we are able to simulate the heterogeneous distribution of water supply and agricultural water demand for irrigation. This allows for identifying regional hot spots of blue water scarcity and explicit shadow prices for water. We generate scenarios based on moderate policies regarding future trade liberalization and the control of livestock-based consumption, dependent on different population and GDP projections. Results indicate increased water scarcity in the future, especially in South Asia, the Middle East, and North Africa. In general, water shadow prices decrease with increasing liberalization, foremost in South-, South-East Asia, and the Middle East. Policies to reduce livestock demand in developed countries do not only lower the domestic pressure on water but also alleviates to a large extent water scarcity in developing countries. However, it is shown that one of the two policy options alone would be insufficient for most regions to retain water scarcity in 2045 on levels comparable to 2005.

[1]Reprinted version from Schmitz, C., H. Lotze-Campen, D. Gerten, J.P. Dietrich, A. Biewald, B. Bodirsky and A. Popp (2012), Blue water scarcity and the economic impacts of future agricultural trade and demand, *in revision for Water Resources Research.*

5.1 Introduction

More than ever before the question of water scarcity shapes debates on current and future food production (Rosegrant et al., 2009; Hanjra and Qureshi, 2010; Godfray et al., 2010). Water scarcity is mainly driven by population growth (Falkenmark et al., 1989; Vörösmarty et al., 2000) and is, from this point of view, a relatively new phenomenon in human history (Kummu et al., 2010). As global population is expected to grow to 9-10 billion by the middle of the 21st century (Lutz et al., 2001), the precondition for increased water scarcity is set. Furthermore, it can be expected that disposable incomes in developing countries will rise (Rosegrant and Cline, 2003) and that food and dietary trends, which have been observed in rich countries over the last decades, are likely to be taken up by most developing societies in the future (Pingali, 2006). This will lead to higher consumption of livestock products (Delgado, 2003) and aggravate stress on water resources as animal-based calories are produced in a much more water-intensive way than plant-based calories (Hoekstra and Chapagain, 2007).

The focus of this study is on blue water, which is defined as the rainfall water escaping evaporation and, therefore, is located in surface water and aquifers (Falkenmark et al., 2007). Several indicators have been developed to measure blue water scarcity. Calculations of water scarcity started with the Falkenmark indicator, relating total freshwater resources to per capita requirements (Falkenmark, 1989). In contrast to the absolute Falkenmark indicator, several relative indicators have been developed computing the water withdrawal-to-availability (WTA) ratio (Vörösmarty et al., 2000; Alcamo et al., 2003; Oki and Kanae, 2006; Islam et al., 2006; Hanasaki et al., 2008b). Smakhtin et al. (2004) went a step further by adding environmental aspects to the WTA analysis. Another group of indicators emphasizes the social dimension of water scarcity. Ohlsson (2000) developed an indicator based on the combination of traditional hydrological indices and the UNDP Human Development Index (HDI) as an approximation for the social adaptive capacity of a society. More comprehensiveness is provided by the watershed sustainability index (Chavez and Alipaz, 2007), where in addition to the HDI, the Water Poverty Index and the Environmental Sustainability Index (ESI) are considered. A first attempt of a rather simple economic water scarcity indicator has been developed by the International Water Management Institute (Molden, 2007). This indicator measures the amount of renewable freshwater resources available for human requirements. The results are clustered into four groups, based on a global status map for freshwater resources. A region is called economic water scarce, if a lack of investment in water infrastructure or a lack of human capacity to satisfy the demand for water is observed.

In our study we look explicitly on agricultural fresh water use since around 70 to 80% of human freshwater withdrawals (Gleick et al., 2009) and around 90% of the consumed blue water (Shiklomanov and Rodda, 2003) are used for agriculture. A specific indicator for agricultural water stress has been recently developed by Vörösmarty et al. (2010). The authors estimated the burden that crop production places on renewable water resources by considering water supply and irrigation water demand. Gerten et al. (2011) follows a similar approach but calculates the WTA ratio based on blue and green water availability; with green water defined as water originating directly from precipitation.

Although all of those indicators have different perspectives on water scarcity, they consistently lack a crucial driving force: the economics of water demand. None of those has an integrated view based on the interplay between biophysical availability of water and economic-driven demand (Sauer et al., 2010). As de Fraiture (2007) points out, the indicators focus solely on the water and biophysical sector and largely ignore macroeconomic drivers, like income, trade and economic policy as well as microeconomic drivers, like production costs and productivity growth. To fill large parts of this gap, we have developed a new agro-economic water scarcity indicator on grid cell level. The indicator is based on the water shadow price generated uniquely through the coupling of a global biophysical vegetation model and an economic land use model. The indicator has the advantage that economic drivers, like production costs, technological change, and trade patterns are included. This allows for analyzing policy actions on a global level taking the economic forces in the land use system endogenously into account. The IMPACT-WATER model (Cai and Rosegrant, 2002), the related WATERSIM model (de Fraiture, 2007) and the GTAP-W model Calzadilla et al. (011b) are attempts to integrate the economics of water into an agricultural modeling framework. However, in contrast to our approach, they are all neither working on a high spatial resolution nor are they directly linked to a biophysical model.

In our analysis we focus on two possible policy areas and their interaction. One is the option of increased food trade via trade liberalisation. Agricultural goods contain a significant amount of so called "virtual water", which is defined as the amount of freshwater embedded in the production process (Hoekstra and Chapagain, 2007). Trading those goods internationally plays an important role for increasing the global efficiency of water use (Fader et al., 2011). Several studies have quantified the importance of current virtual water trade and demonstrated that already today some water-scarce regions are major importers of water-intensive products (Konar et al., 2011; Fader et al., 2011; Hanasaki et al., 2010; Chapagain and Hoekstra, 2008; Hoekstra and Hung, 2005; Oki and Kanae, 2004). However, in contrast to virtual water assessments, we explicitly analyze the effects of different trade liberalisation scenarios on agro-economic water scarcity and assess the impact on future water scarcity.

The second policy parameter enforces a changing diet towards lower consumption of livestock products. At the turn of the millennium around two billion people based their diets largely on animal products whereas more than four billion people lived primarily on a plant-based diet (Pimentel and Pimentel, 2003). No global study has assessed the impact of changing this relation towards more plant-based diets on global water resources in detail. Gerten et al. (2011) recently assessed the sensitivity of their results by calculating the likelihood of countries to be water scarce under a scenario of lower animal calorie intake. Renault and Wallender (2000) analyzed in a simple regional model the percentage of additional water which is saved according to different scenarios until 2025. Apart from those studies, the influence of changing diets has been either shown globally on land use (Wirsenius et al., 2010) and greenhouse gas emissions (Popp et al., 2010; Stehfest et al., 2009) or regionally on water consumption, like for China (Liu and Savenije, 2008). Finally, in order to evaluate the sensitivity of the simulations, we run the model with different population and GDP scenarios.

We start our analysis by describing the involved models, the creation of the agro-economic water scarcity indicator, and the scenario implementation. Furthermore, water-related input data, i.e. water discharge and irrigation demand, from the dynamic global vegetation and water balance model LPJmL (Lund-Potsdam-Jena managed Land) (Bondeau et al., 2007) are compared with the outcome of the global water resources model H08 (Hanasaki et al., 2008a,b). In section 5.3 we present the outcome of the scenarios with a special attention to water shadow prices, technological change rates, and land use changes as well as the sensitivity of those. Subsequently, we discuss methods and results in relation to previous studies. In the section 5.5 we draw conclusions and policy implications from our analysis.

5.2 Modeling approach and methods

5.2.1 Model descriptions

The MAgPIE model

For the analysis in this paper we use MAgPIE ("Model of Agricultural Production and its Impact on the Environment"), a nonlinear recursive dynamic optimization model (Lotze-Campen et al., 2008, 2010; Popp et al., 2010; Schmitz et al., 2012). It is coupled to a grid-based dynamic vegetation model (see section 5.2.1), to simulate spatially explicit land and water use patterns. This approach provides a high flexibility to integrate various types of biophysical constraints into an economic decision-making process. The dual solution of the economic optimization model MAgPIE allows for computing shadow prices (or implicit economic values) for binding constraints on grid cell basis. The shadow prices define the potential cost savings the model would achieve by relaxing the constraint by one unit. In this study we focus on the water shadow price, which reflects the implicit economic value for one additional cubic meter of water in a particular grid cell (see section 5.2.2).

Each cell of the geographic grid is assigned to one of the ten economic world regions (Appendix 2). The regions are initially characterized by data for the year 1995 on population (CIESIN et al., 2000), gross domestic product (GDP) (World Bank, 2001), food energy demand (FAOSTAT, 2010), average production costs for different production activities (Narayanan and Walmsley, 2008), and current self-sufficiency ratios for food (FAOSTAT, 2010). While all supply-side activities in the model are grid-cell specific, the demand side is aggregated to the regional level. Future demand of calories and the share of livestock products are dependent on income and population and are based on a detailed regression analysis (Figure 5.1 and Appendix 3).

To allocate the demand to the supply regions, international trade is considered in MAgPIE by using flexible minimum self-sufficiency ratios at the regional level. Self-sufficiency ratios describe how much of the regional agricultural demand quantity is produced within a region. For instance, a ratio for cereals of 0.8 means that 80% of cereals is produced domestically, whereas 20% is imported. Two virtual trading pools are implemented in the model which allocate global demand to the different supply

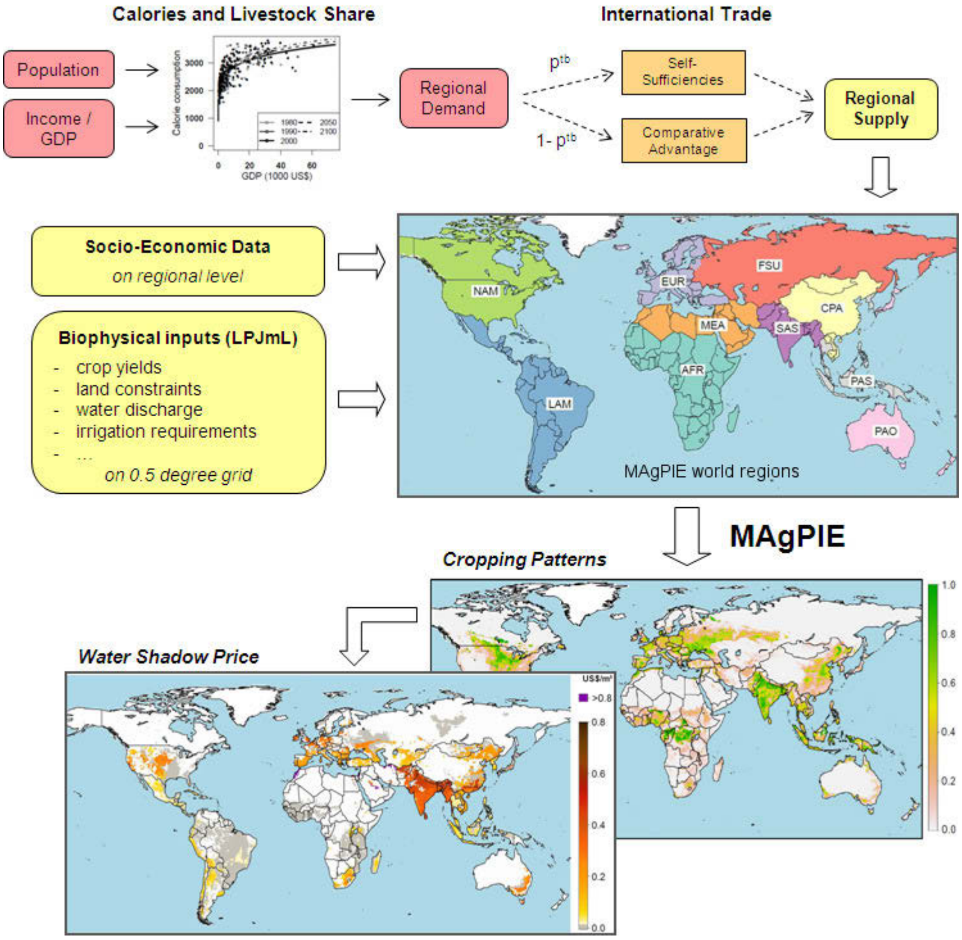


Figure 5.1: Simplified MAgPIE flow chart of key processes highlighted in this study (demand and trade implementation, data inputs from LPJmL and spatially explicit water shadow price). With exogenous data about population and GDP development, we calculate regional demand and the livestock share. The former is then translated to regional supply depending on the international trade scenario. Further inputs for MAgPIE are socio-economic data like production costs and biophysical inputs from LPJmL. After the optimization of MAgPIE, one of the outputs are cropping patterns of the different crops, which are the basis for the water shadow price.

regions (Figure 5.1). The demand which enters the first pool is allocated according to fixed criteria. Self-sufficiency ratios based on FAO food balance sheets (FAOSTAT, 2010) determine how much is produced domestically, and export shares (FAOSTAT, 2010) determine the share of each region in global exports. The demand which enters the second pool is allocated according to comparative advantage criteria to the supply regions. This means that the region with the lowest production costs per ton will export. The parameter p_{tb} defines the share of trade which flows into both pools. If p_{tb} is equal to 1, the total demand will be distributed according to fixed self-sufficiencies and export shares to the supply regions. If p_{tb} is equal to 0, all trading quantity will end up in the second pool and is distributed according to comparative advantage criteria to the supply regions. More details of the implementation are provided in Schmitz et al. (2012) and in chapter 3.2.3.

The resulting demand calories are produced by 16 cropping activities and 5 livestock activities (see Appendix 2). The five livestock activities depend on specific feed energy requirements, which consist of a mixture of pasture, fodder, and food crops. All these inputs are specific for each region and animal type and are based on minimum requirements for maintenance, growth, lactation, reproduction and other basic biological needs. Finally, general allowances for basic activity, temperature effects, and the use of extra energy for grazing are differentiated. All data are based on Wirsenius (2000) and further details concerning the implementation in MAgPIE are given in Weindl et al. (2010).

For future projections the model works on time steps of 10 years in a recursive dynamic mode. The optimized land use pattern from one period is taken as the initial land constraint for the consecutive period. MAgPIE minimizes global costs, consisting of four different cost categories: First, production costs, containing factor costs for labour, capital, and intermediate inputs, are taken from GTAP (Narayanan and Walmsley, 2008). Production costs per area unit evolve with the yield level in a linear relationship (Schmitz et al., 2010). Second, investments in yield-increasing technological change increase exponentially based on the state of agricultural development of a region (Dietrich et al., 2012; Schmitz et al., 2010). This endogenous implementation allows MAgPIE to project future yield increases and the costs involved. In terms of water, technological change increases demand for blue water, since water requirements are dependent on yield. Third, costs for land expansion which is the other alternative for MAgPIE to increase food production (Krause et al., 2009; Popp et al., 2011a) and costs for irrigation area expansion are considered. Land conversion costs (for preparation of new land and basic infrastructure investments) are based on country-level marginal access costs generated by the Global Timber Model (GTM) (Sohngen et al., 2009). Additionally, expansion of irrigation area involves aggregated, regional-based costs taken from the AQUASTAT-Database (FAO, 2011a). Fourth, intraregional transport costs accrue for every commodity unit as a function of the distance to intraregional markets and the quality of the infrastructure. The data set is based on GTAP transport costs (Narayanan and Walmsley, 2008) and a 30 arc-second resolution data set on travel time to the nearest city (Nelson, 2008).

A mathematical description of the model is provided in the supplementary materials.

The LPJmL model

Biophysical inputs for MAgPIE, like potential crop productivity and related water use as well as land and water constraints are supplied for each grid cell by the Lund-Potsdam-Jena dynamic global vegetation and water balance model with managed Land (LPJmL) (Bondeau et al., 2007). LPJmL endogenously models the dynamic processes linking climate and soil conditions, water availability and plant growth, and takes the impacts of CO_2, temperature and radiation on yield directly into account. For this study, however, those inputs are not subject to any climate change impacts. LPJmL also covers surface and subsurface water flows (though without explicit distinction of groundwater), as carbon and water-related processes are closely linked in plant physiology. Also blue and green water consumption is separated, with the former occurring on areas equipped for irrigation(Döll and Siebert, 2000), which allows for distinction of rainfed and irrigated yields. Whereas green water originating directly from precipitation is taken up by plants and the soil, blue water is the amount of productively or unproductively evapotranspiring irrigation water that originates e.g., from river segments, aquifers, lakes and reservoirs (Gerten et al., 2004). The computation of blue water stocks and flows and the separation of green and blue water flows on irrigated areas in LPJmL are described in detail in Rost et al. (2008). Irrigated areas receive their additional water from the natural runoff and its downstream movement according to the river routing in LPJmL (see Rost et al. (2008) for a detailed description of the river routing module in LPJmL). The water discharge value for each grid cell from LPJmL is used as a constraint for irrigation in MAgPIE. From a modification of the MIRCA2000 land use dataset (Portmann et al., 2010), the information about irrigated and rainfed land use fractions is derived (Fader et al., 2010).

5.2.2 Blue water implementation and related shadow price

The implementation of blue water in MAgPIE is based on data inputs from LPJmL. LPJmL delivers two relevant cell-specific water inputs for MAgPIE: Firstly, blue water discharge available to the agricultural sector, and secondly, the water requirement per plant and cell which is needed from irrigation. For this analysis we compared those inputs with the outcome of an independent hydrology model. The water discharge from LPJmL is reduced in MAgPIE by an efficiency factor which represents the losses in the water and irrigation system. Finally, the water shadow price can be determined based on the water demand per cell calculated in MAgPIE.

Comparison of water inputs

Both LPJmL inputs, blue water discharge and water requirement per plant, are crucial factors for the analysis. For an evaluation we, therefore, use analogous results from the H08 model, which similar to LPJmL provides water withdrawal values specifically for agriculture on a grid cell level (Hanasaki et al. (2008a) and applied in Hanasaki et al. (2008b)). For the comparison we computed the WTA ratio from both models, where the model runs are based on climate projections from the general circulation model

ECHAM5 (Roeckner et al., 2003) and SRES A2 (Special Report on Emissions Scenarios) (Nakicenovic and Swart, 2000). We followed the approach by Vörösmarty et al. (2010) and ranked it relatively to the highest value. This means the highest value is equal to 1 whereas the lowest value is almost 0. In total, 14,382 cells of 59,199 cells contain a WTA ratio in both models. With the help of the map comparison kit (Visser and de Nijs, 2006), which allows for the numerical comparison of two different maps, we compared both maps. The comparison index c is calculated by taking the difference of both model indices on cell level j.

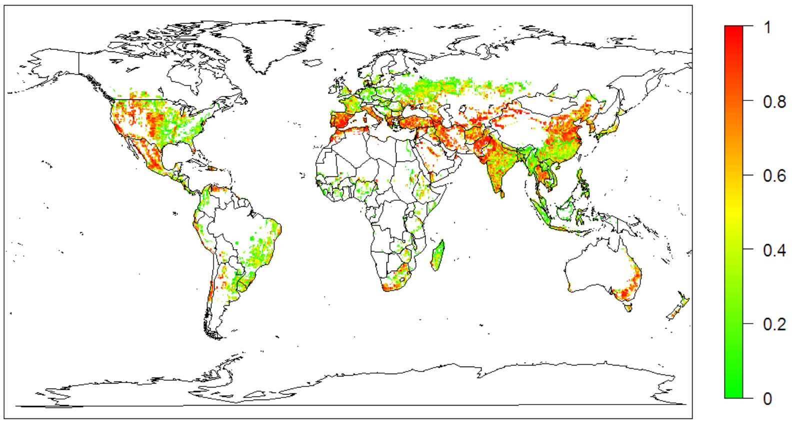
$$c_j = H08_j - LPJmL_j \tag{5.1}$$

Figure 5.2(a) illustrates the ranked agricultural WTA ratio calculated for the LPJmL model and the graph in the middle for the H08 model. Highest values are modeled for South-East Australia, Northern China, North India, Pakistan, the Middle East, North Africa, Southern Europe, and parts of the United States and Mexico. The map in the middle shows the same for H08 model (Figure 5.2(b)).

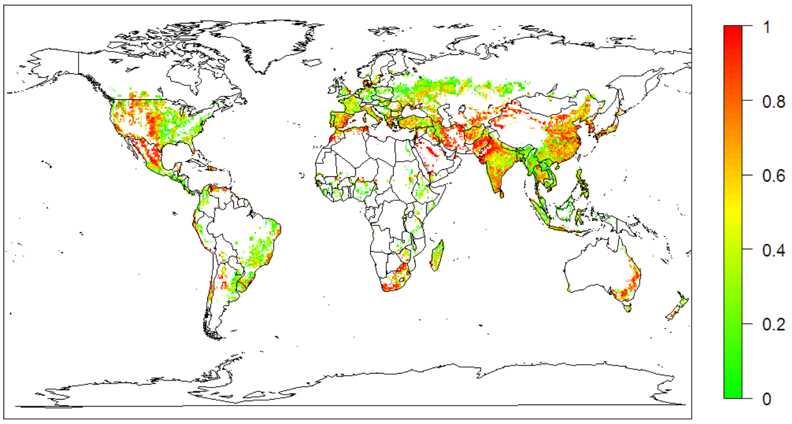
Figure 5.2(c) shows the difference of the ranked WTA ratio between the H08 model and the LPJmL model. Largest differences are noticed for Southern Europe and Turkey, where LPJmL has higher WTA values and for Southern China, where LPJmL has lower values than H08. The validation discloses that both data sets, although independently derived (LPJmL is primarily a vegetation model, while H08 is a specialized hydrology model), the outcomes are very similar. Comparing the LPJmL outputs with the recently published indicator by Vörösmarty et al. (2010), it appears that the LPJmL values are higher in Western USA and Middle East and lower in Central Asia and Argentina, whereas the remaining regions are similar.

Irrigation efficiency

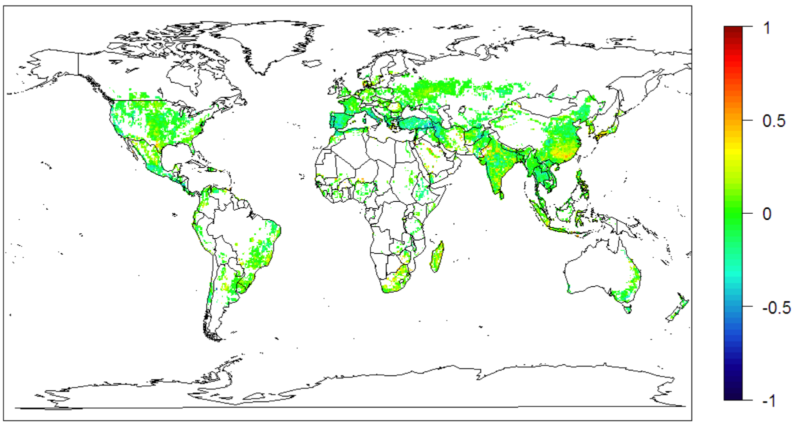
Improving irrigation efficiency is one of the main options to reduce water demand (Molden, 2007). Over 50% of global water resources which are intended for irrigation are lost due to bad management, losses in the conveyance system and inefficient application to the plant (Rogers et al., 1997). In MAgPIE, irrigation efficiency is implemented through an efficiency factor which comprises management, conveyance, and application efficiency. The specific efficiency levels for 1995 are calculated on country level based on Rohwer et al. (2007). In contrast to most other studies, irrigation efficiency in MAgPIE is a dynamic input. In order to project future irrigation efficiencies, we tested several hypotheses concerning the relationship between the efficiency factor and independent variables, like GDP per capita (Heston et al., 2011), irrigation area share (Döll and Siebert, 2000) and the level of agricultural intensity (Dietrich et al., 2012). Cross-sectional regression analyses with different functional forms reveals that only GDP per capita is significant as explanatory variable for irrigation efficiency. For the analysis we included 149 countries with documented irrigation areas. However, in order to reduce data errors by small countries (with respect to irrigated agriculture), those below an irrigation area share of 5% of total cropland and an absolute irrigation



(a) Relative ranked WTA ratio of the LPJmL model



(b) Relative ranked WTA ratio of the H08 model



(c) Comparison between ranked WTA ratio of LPJmL and H08 model

Figure 5.2: Upper and central map: Relative ranked ratio of water withdrawal-to-availability (WTA) of the LPJmL model (a) and the H08 model (b) in 1995. Values of both graphs are displayed as share compared to the highest rank with 1 as the highest value and 0 the lowest. Lower map: Comparison between ranked WTA ratio of LPJmL and H08 model.

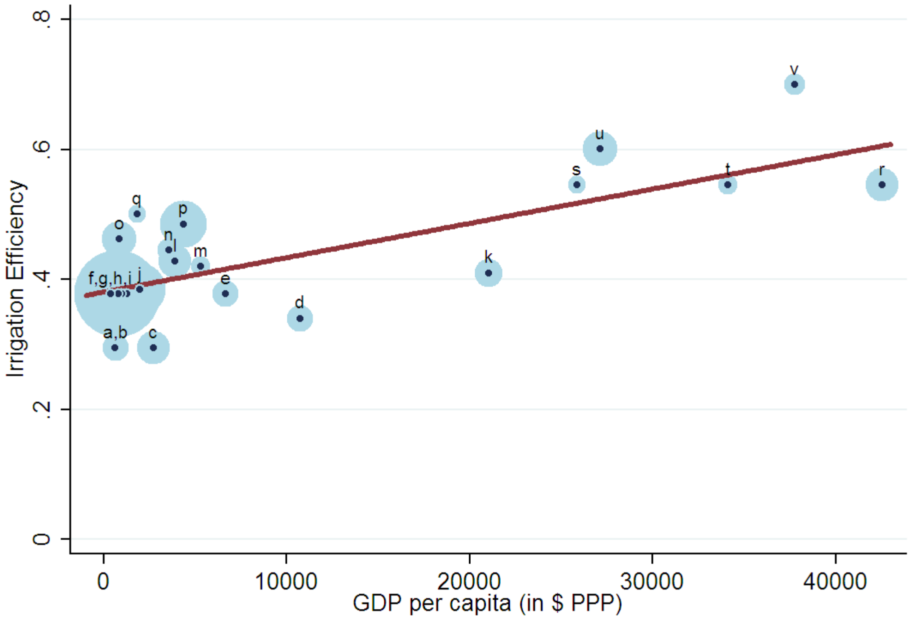


Figure 5.3: Regression between irrigation efficiency and GDP per capita (in $PPP/capita)

area of 10,000 ha were clustered together to 9 world regions. Together with the 13 countries, which fulfilled the minimum criteria, 22 data points have been used for the regression.

The regression determines the following linear relationship between level of economic development (measured in GDP per capita $\frac{gdp_i}{pop_i}$) and irrigation efficiency η on regional level i:

$$\eta_i = 0.381 + (\frac{gdp_i}{pop_i}) \cdot 5.28 \cdot 10^{-6} \tag{5.2}$$

The results of the weighted linear regression gave an adjusted R^2 of 0.55, but highly significant p-values of the t-tests for the constant and the slope (p = 0.000). The conducted regression specification error test (RESET) (Ramsey, 1969) offers a high significance level which means that no important variables seem to be omitted ($F[3, 18]$ = 1.59 and $F_{0.05}$ = 3.16). Figure 5.3 shows the graph of the regression analysis with the corresponding countries and regions[2].

The irrigation efficiencies increase over time due to increasing GDP per capita in all

[2] a = Vietnam, b = Pakistan, c = Thailand, d = Central America, e = Turkey, f = Bangladesh, g = Indonesia, h = India, i = Philippines, j = Central Asia (incl. China), k = Rest of South Asia, l = Rest of Former Soviet Union, m = Malaysia, n = Middle East/North Africa, o = Sub-Saharan Africa, p = South America, q = Ukraine, s = Spain, r = North America, t = France, u = Rest of Europe, v = Pacific OECD Countries

regions (Figure 4 in Appendix 3). Highest efficiencies are achieved in developed regions, like NAM (from 56% in 2005 to 67% in 2045) and EUR (from 48% to 60%) and PAO (from 51% to 62%). Europe is behind North America, since the Eastern European countries have very low values. Sub-Saharan Africa (40%) and South Asia (42%) have the lowest efficiencies in 2045.

Finally, in MAgPIE available water for irrigation p^{water} is calculated on cell level j by the product of water discharge $p^{discharge}$ and the regional specific irrigation efficiency η_i.

$$p_j^{water} \leq p_j^{discharge} \cdot \eta_i \tag{5.3}$$

Water shadow price

Since MAgPIE is an economic optimization model operating under constrained conditions, it is possible to generate a shadow price for every specified constraint. The shadow price is defined as the achievable rate of increase in the objective function per unit increase in resource x (Aucamp and Steinberg, 1982). Since our objective function minimizes costs, we have to reframe the definition to "the achievable rate of decrease in the objective function if the constraint x is relaxed by one unit". For our analysis we use the available water constraint p_j^{water}.

$$wsp_j = \frac{\partial g_t^*}{\partial p_j^{water}} \tag{5.4}$$

where wsp_j stands for the water shadow price in each cell j and g_t^* denotes the optimal value of the goal function. For a definition of the water constraint and the goal function we refer to the mathematical description in the supplementary materials. In economic terms wsp is defined as the saved marginal costs, when one additional unit of water would be available in a particular grid cell. With cell-specific water shadow prices we are able to generate maps in order to define hot spots of water scarcity under different future scenarios.

5.2.3 Scenario definition and sensitivity analysis

We consider one reference scenario and three policy scenarios which are based on medium population and GDP (Gross Domestic Product) projections. The reference scenario is based on the description in section 5.2.1. It is assumed that 50% of the intact and frontier forest (which is mainly the rainforest in South America, Central Africa and Pacific Asia) must be saved until 2045. Furthermore, we do not model any climate change impacts in this study. The three policy scenarios differ from the reference scenario in their policies regarding trade liberalisation and the consumption of livestock products (Table 5.1). We created those scenarios with the aim to consider a range of future policies and, therefore, we chose moderate scenarios. This contrasts with many other studies, which usually present extreme scenarios in order to characterize the possible theoretical range.

Table 5.1: Scenario Definition

Scenarios		**Demand Pattern**	
		BAU Diet	Fair Diet
Trade Liberalisation	bilateral	reference (0)	livestock (2)
	global	trade (1)	trade-livestock (3)

Table 5.2: Trade barrier reduction factor in the two trade scenarios over time

Scenario	2005	2015	2025	2035	2045
bilateral trade liberal.	1	0.975	0.951	0.927	0.904
global trade liberal.	1	0.9	0.81	0.729	0.656

We assume two different trade policies (c.f. Schmitz et al. (2012)). The bilateral trade implementation reflects the case that no new global trade agreement is implemented. It reflects largely the situation under the Doha WTO (World Trade Organization) Negotiation Round of the past decade, during which a joint trade agreement could not be agreed upon. In contrast, our global trade policy assumption follows a historically derived pathway of trade liberalisation considering the two decades before the Doha Round (1980-2000). Taking into account various literature sources we decided that a 10% trade barrier reduction each decade until 2045 reflects a plausible policy scenario (Healy et al., 1998; Conforti and Salvatici, 2004), if global trade agreements are successful in the future. This is also supported by the general trade study of Dollar and Kraay (2004), who found a 22% tariff cut for non-globalizing countries, 11% for globalizing countries, and 0% for rich countries between the 1980s and 1990s. Table 5.2 displays the development of the trade balance parameter over time in the different trade implementations.

In the business-as-usual diet scenario (BAU diet) no policy to limit animal consumption is assumed and the consumption share of livestock products depends on the GDP per capita scenarios (see Appendix 3). In the second case, a fair diet is assumed, where a global policy enforce an equal share of livestock and fish products of 20% per capita in every world region, which evolves continuously until 2045. The 20% share of livestock-based calories is taken as threshold, since it is considered as a realistic, fair, and healthy diet (Pimentel and Pimentel, 2003). Although there is a lively scientific debate around this topic and other studies suggest that a pure vegetal-based diet would be even the healthiest (Campbell and Campbell, 2006), we take the 20% share as a policy target which is realistic to achieve in 2045. Figure 3 in Appendix 3 shows the animal-based calorie share for the period 2005-2045 in both scenarios.

The outcome of the model depend to a large extent on the food demand requirements, which in turn depend on the respective population scenarios and on a regression with GDP per capita (see Appendix 3). In order to reveal the sensitivity and variation in the results we apply a combination of three different UN population (United Nations, 2011) and three different GDP scenarios which results in nine different scenarios for food demand (Table 4). From these we take one (scenario E) as default scenario for the analysis and the remaining eight as sensitivity scenarios. For the methodology, we refer to Appendix 3.

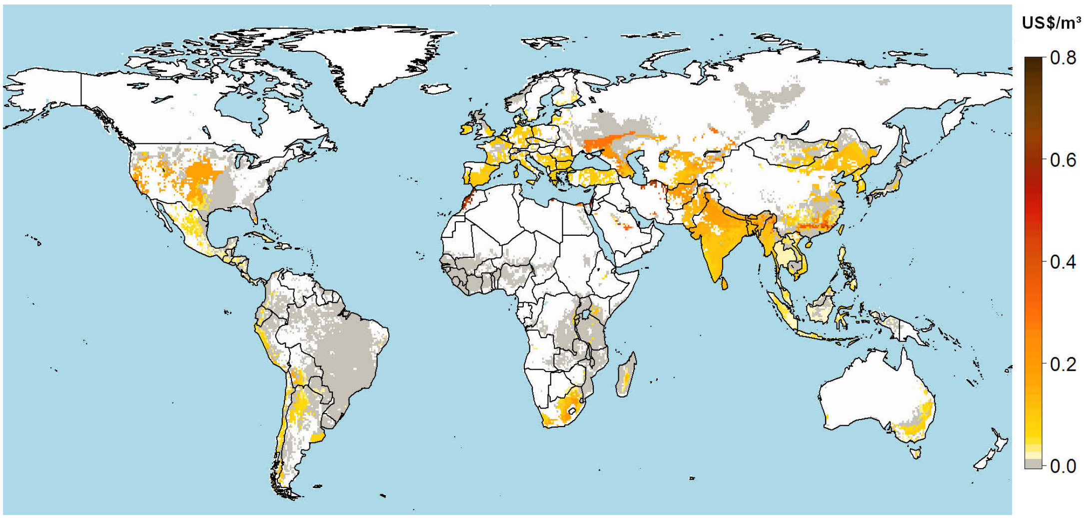
5.3 Scenario results

5.3.1 Water shadow price

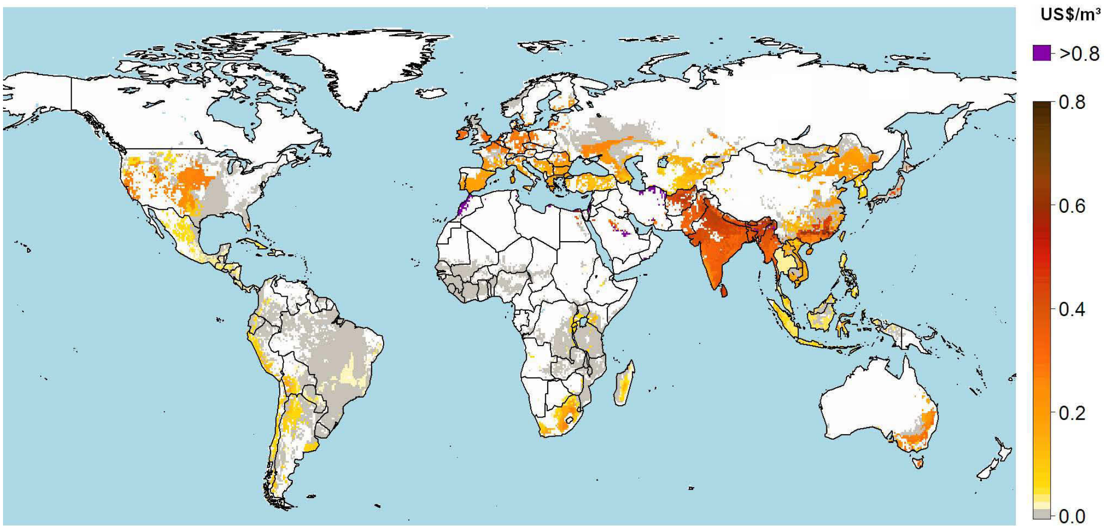
The cell-specific water shadow price (WSP) of MAgPIE is plotted for the years 2005 (Figure 5.4(a)) and 2045 (Figure 5.4(b)) on a 0.5 grid basis. We note three regions, South Asia (India, Bangladesh, Pakistan, and Afghanistan), North Africa (Morocco, Algeria, and Egypt) and the Middle East (with Israel, Saudi Arabia and Iran), where the water shadow price is expected to reach much higher levels in the future. Foremost, blue water scarcity in countries like Morocco, Israel and Iran increases in the model runs from around 0.7 US$/m^3 in 2005 to up to 2 US$/m^3 in 2045. Almost the whole area of South Asia is projected to face an increase in water scarcity within the coming decades given the fact that the water shadow price is growing to values of 0.6 US$/m^3 or even higher. Significant higher levels can be also expected in South-Eastern Australia, North-East and South-East China, Japan, and Europe. In Europe, the highest water shadow prices are supposed to appear in countries such as France or Germany, but also in Southern Europe water scarcity is supposed worsen. The South East of Australia and Japan as well as the Eastern part of China are expected to experience an explicit increase in water shadow price up to 0.3 to 0.4 US$/m^3. On the other hand, there are also some regions, as for example a large part of South America or the South East of Africa where model simulations indicate that enough freshwater would be available in the future compared to irrigation demands resulting in a water shadow price equal to zero.

Figure 5.5 presents the differences in cell-specific water shadow prices in the three policy scenarios (1-3) compared to the reference scenario (0) in the year 2045 (lower graph in Figure 5.5). Starting with the trade scenario (1), four regions (South Asia, Middle East/North Africa, South East Australia, and Japan) reveal striking results. In South Asia and Middle East/North Africa the water shadow price is expected to decrease in almost the whole region by up to 0.3 US$/m^3. In contrast, in South East Australia and Japan the price is going to rise by around 0.1 US$/m^3 or 0.2 US$/m^3, respectively. Furthermore, in Central Asia (mainly Kazakhstan) and some parts of China, USA and Southern Africa small rises are obtained. In Europe water shadow prices moderately drop and even less so in large parts of mid and western USA.

In the livestock scenario (2) the water shadow price decreases in all countries, except for Japan and to a small extent in countries of Southern Africa. Highest decreases are obtained particularly in Europe and Western USA as well as in Southern China. This means that the water shadow price in Australia and Central Asia increases in the trade scenario (1) and decreases in the livestock scenario (2). However, in the combined trade-livestock scenario (3), Southern Africa reveals decreasing water shadow prices and only in Japan prices increase even further. Comparing the third with the second scenario



(a) Cell-specific water shadow price in 2005



(b) Cell-specific water shadow price in 2045

Figure 5.4: Cell-specific water shadow price for the reference scenario in 2005 (upper map) and 2045 (lower map) on a 0.5 grid basis. White cells do not consist of any cropland equipped for irrigation. Grey cells contain irrigation area but the water shadow price is zero.

shows that in South Asia with countries like India, Afghanistan and Bangladesh the price decrease is highest, followed by Southern China, whereas in Europe, USA, Latin America, North China and Australia the differences are only marginal.

In order to stress the differences of the WSP in the different scenarios in 2045 and the sensitivity of those simulations, we aggregated the price on regional level. The regional water shadow price in the reference scenario in 2045 (Figure 5.6) is highest in SAS with a price of almost 0.38 US$/m^3, followed by MEA with almost 0.22 US$/m^3, EUR with 0.16 US$/m^3 and CPA with 0.08 US$/m^3. All other regions have water shadow prices below 0.04 US$/m^3. Conspicuously low water shadow prices are projected for AFR and LAM with less than 0.01 US$/m^3. The boxplots display the variation (minimum, lower quartile, median, upper quartile and maximum) due to the nine different population and GDP sensitivity scenarios. The variations are rather moderate, given the large variation in the applied sensitivity scenarios, and the order of regions is almost not influenced by them. Largest variations are obtained for the three regions with the highest water shadow price (EUR, MEA, and SAS). In the case of SAS the maximum value is 0.53 US$/m^3 and the lowest value is 0.26 US$/m^3.

Figure 5.7 emphasizes the difference in regional water shadow price in 2045 in the three policy scenarios (1-3) versus the reference scenario (0). Presenting absolute changes, in all regions and all scenarios the shadow prices decrease or stay constant. The only exception is the region PAO, where the price increases by 0.02 US$/m^3 in the trade scenario (1). We obtain again for SAS and MEA the highest decreases. In both regions the trade scenario (1) shows stronger reductions of the water shadow price than the livestock scenario (2). The opposite is found for EUR, CPA, PAO, and NAM. In these regions the combined trade-livestock scenario (3) demonstrates a lower reduction than in the livestock scenario (2) with only bilateral trade liberalisation. In contrast, SAS with -0.31 US$/m^3 and MEA with -0.21 US$/m^3 have the highest reductions in the combined scenario (3). PAS resembles SAS and MEA as the livestock scenario (2) causes the lowest decrease and the combined scenario the strongest decrease (-0.02 US$/m^3), but with much lower rates. For FSU we observe only minor changes, and values in AFR and LAM do not change at all. The sensitivity of the results is generally moderate, except for MEA and SAS in the first scenario, for EUR in the second scenario and for all three in the third scenario. The highest reduction is found for SAS in the combined scenario (3) with a value of -0.41 US$/m^3.

5.3.2 Technological change and land use change

Figure 5.8 displays average annual technological change (TC) rates for the ten world regions in the reference scenario. MEA has the highest TC rates over this period with an average annual rate of 1.9%. AFR, CPA, and SAS have high rates as well with values over 1%. EUR and PAO have the lowest values. The rate depends to a considerable extent on the future population and GDP growth as the boxplots show; in some regions less (e.g. LAM and FSU) in some regions more (e.g. MEA, SAS, and PAS).

In Figure 5.9 we present the differences in the regional technological change (TC) rates (presented in percentage points [pp]) of the three policy scenarios compared to the

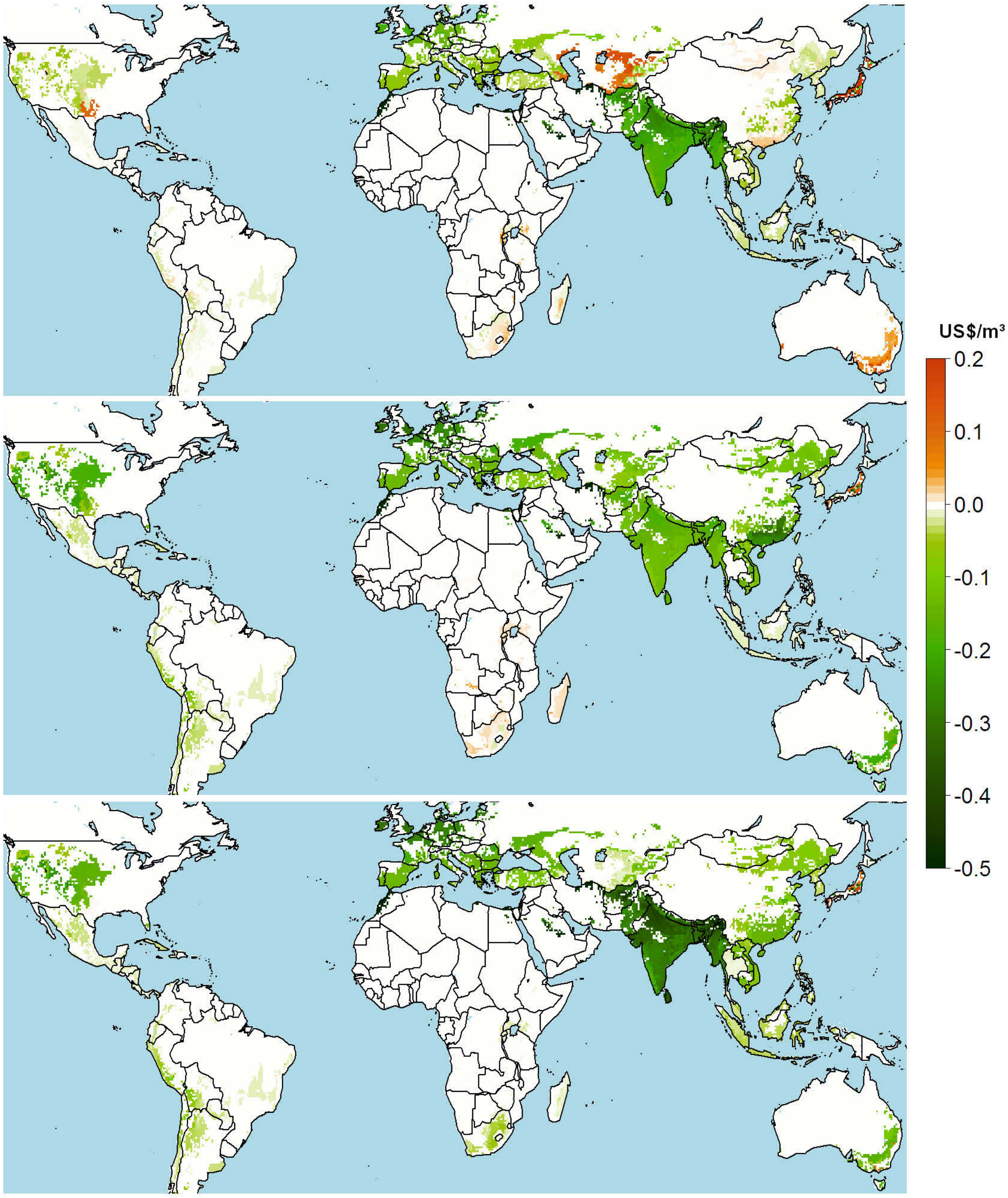


Figure 5.5: Differences in the cell-specific water shadow price in the scenarios 1-trade (upper map), 2-livestock (central map) and 3-trade-livestock (lower map) compared to the reference scenario (0) in 2045 on a 0.5 grid basis

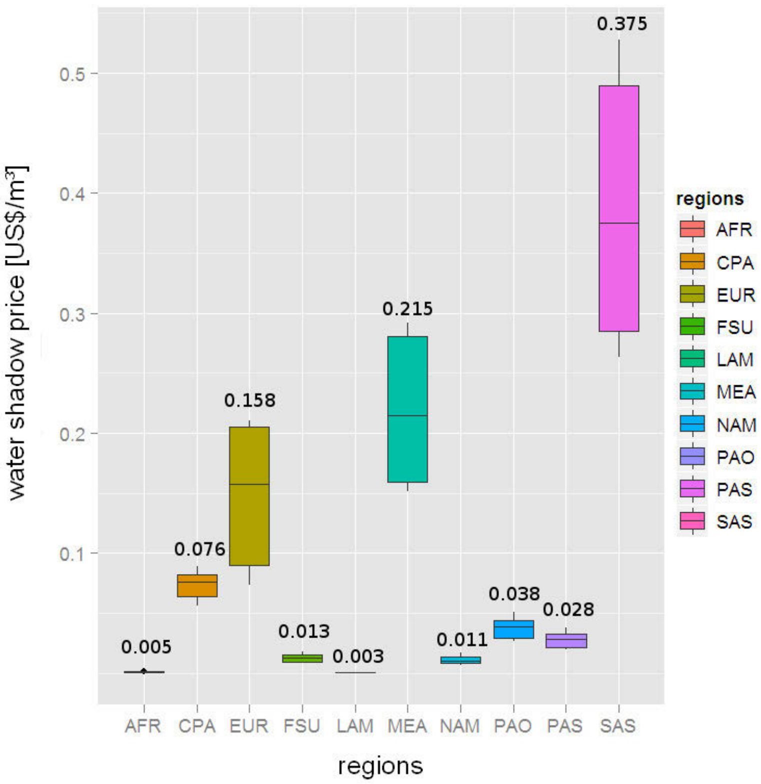


Figure 5.6: Sensitivity of regional water shadow prices (in US$/m^3) in 2045 for the trade, livestock and combined scenario under consideration of 9 different population and GDP sensitivity scenarios. The boxplots display minimum, lower quartile, median, upper quartile and maximum. Above the boxplots the value of the default scenario is given.

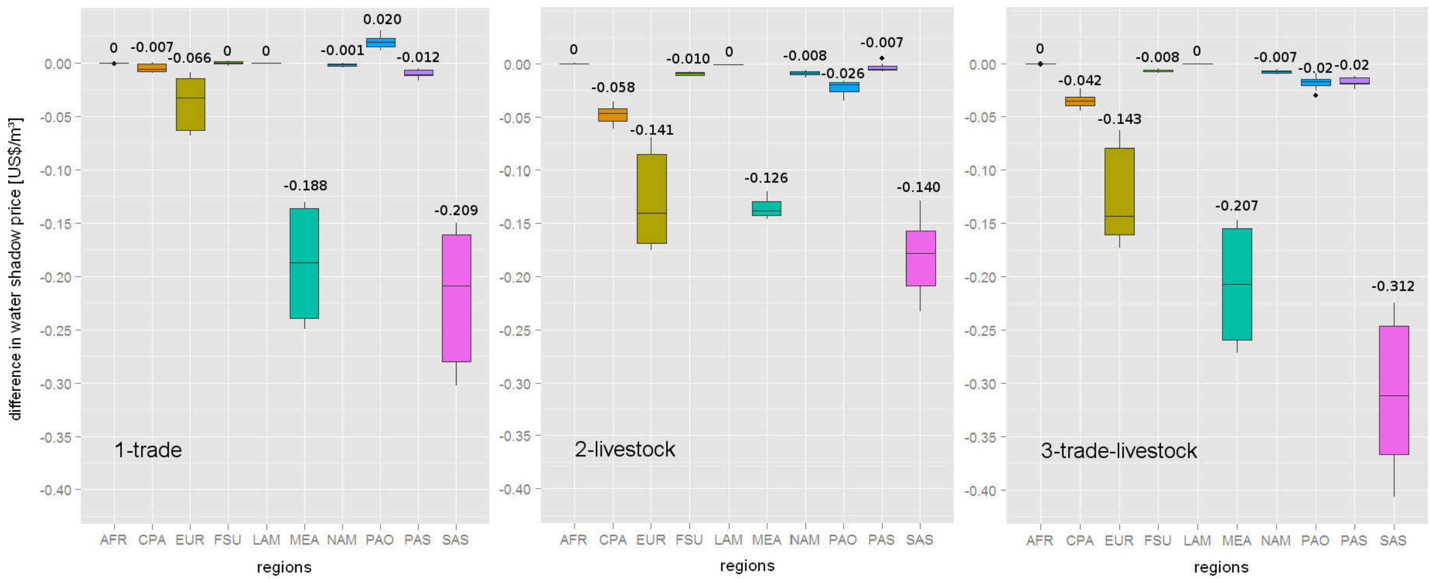


Figure 5.7: Sensitivity of the difference in regional water shadow price in 2045 under 9 different population and GDP sensitivity scenarios. The boxplots display minimum, lower quartile, median, upper quartile and maximum. Above the boxplots the value of the default scenario is given.

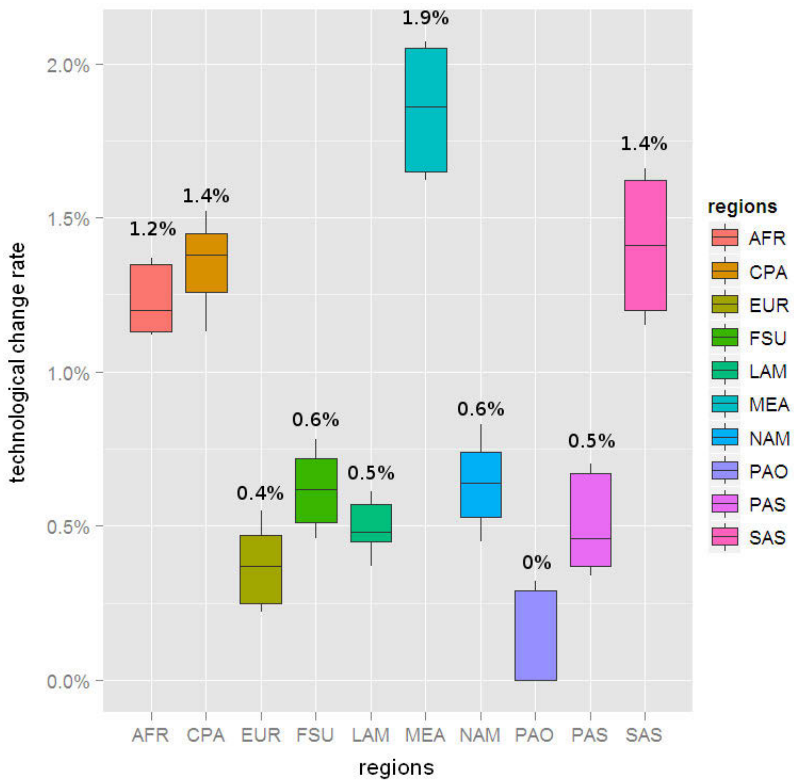


Figure 5.8: Sensitivity of technological change rates in 2045 under 9 different population and GDP sensitivity scenarios. The boxplots display minimum, lower quartile, median, upper quartile and maximum. Above the boxplots the value of the default scenario is given.

Table 5.3: Total cropland expansion (in mio. ha) from 2005 until 2045 and total cropland (in mio. ha) in 2045

Scenario	Expansion					Total Cropland
	2005	2015	2025	2035	2045	2045
$0 - reference$	104	74	60	59	51	1,648
$1 - trade$	103	37	49	51	39	1,580
$2 - livestock$	53	69	60	36	7	1,526
$3 - trade - livestock$	53	41	40	11	10	1,456

reference scenario over the period 2005-2045. The most notable region is MEA showing decreases of up to 1 pp in the two global trade liberalisation scenarios. In the livestock scenario (2), however, TC rates are reduced by less than 0.5 pp. A similar behavior can be expected in SAS, although the reductions in TC are not as high as in MEA, reaching up to 0.84 pp in the combined trade-livestock scenario (3). In CPA, EUR and NAM TC rates are estimated to decrease stronger in the livestock scenario (2) than in the trade scenario (1). In contrast, FSU faces a similar decline of between 0.32 and 0.35 pp in all three policy scenarios. Two regions, AFR and PAO, are supposed to have rising TC rates within specific scenarios. In AFR, the fair livestock consumption implies rising TC rates of almost 0.2 pp from 2005 to 2045, whereas in the two scenarios involving trade liberalisation decreasing rates of 0.25 pp occur. PAO, however, encounters increasing TC rates (+0.5 pp) for the trade scenario (1) and constant rates for the other two scenarios. Finally, PAS is the only region where the trade scenario causes the lowest TC rates compared with the reference scenario and the other two policy scenarios. The sensitivity due to different population and GDP scenarios is lowest in the trade scenario, where only LAM and PAO show high variations and highest in the combined scenario, where all regions except AFR, CPA, and LAM face considerable variations.

Another option for MAgPIE to increase total production, besides technological change, is to expand cropland. Table 5.3 illustrates the change in total cropland over time and the total cropland in 2045 (in mio. ha). In 2005 the difference of a livestock control policy becomes apparent. With lower livestock consumption cropland expansion is only half compared to the scenarios with business as usual consumption. However, in 2015 and 2025 the expansion increases further in the livestock scenario but decreases from 2035 on. Highest total expansion (+348 mio. ha) is obtained in the reference scenario and lowest in the combined trade-livestock scenario (+156 mio. ha). The sensitivity of those values against different GDP per capita scenarios is low. The highest value for total cropland in the reference scenario in 2045 is 1,711 mio. ha and the lowest is 1,591 mio. ha. The variations in the policy scenarios are slightly higher. For instance, in the combined scenario the highest value is 1,537 mio. ha and the lowest is 1,372 mio. ha. In terms of area equipped for irrigation, we obtain an increase of 14% in the reference scenario until 2045, 11% in the trade scenario, 7% in the livestock scenario and only 1% in the combined scenario.

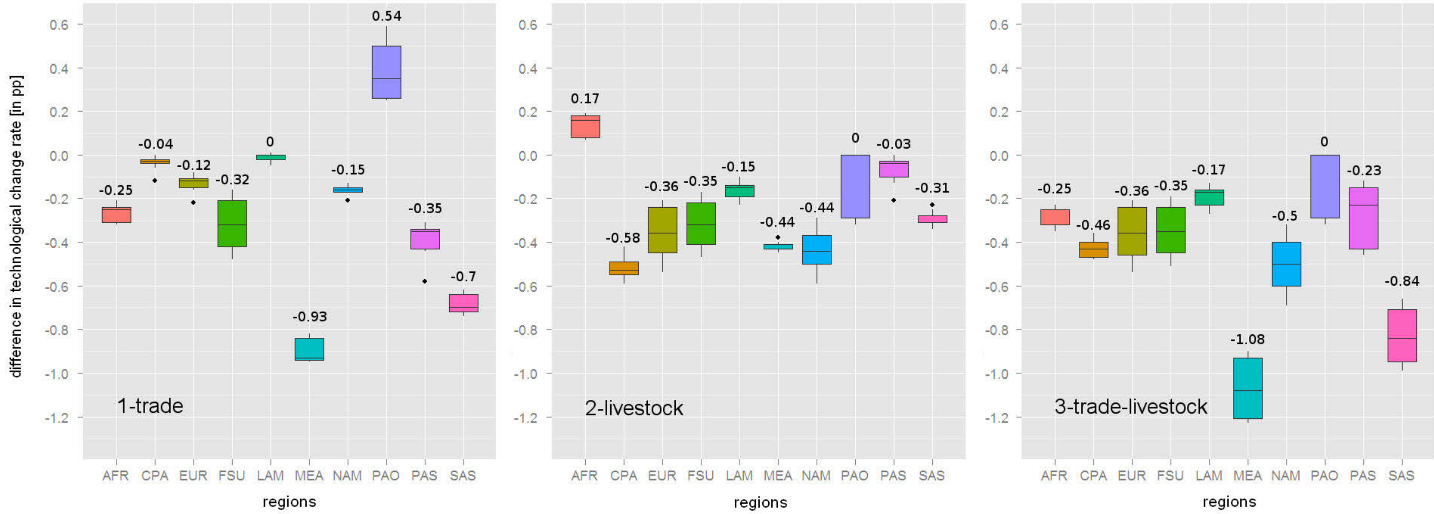


Figure 5.9: Sensitivity of the difference in technological change rates in 2045 under 9 different population and GDP sensitivity scenarios. The boxplots display minimum, lower quartile, median, upper quartile and maximum. Above the boxplots the value of the default scenario is given.

5.4 Discussion

The fact that water availability depends on agriculture (and not only vice versa) has only recently become part of the public perception. The increasing pressure of agriculture on water has its origin in the extensive population growth and the resulting increase in food production during the last century (Falkenmark et al., 1989; Vörösmarty et al., 2000; Kummu et al., 2010). As we expect a further increase in population and an even more dramatic increase in agricultural demand, the pressure on water resources will rise considerably throughout the coming decades. In order to quantify this relationship, we have developed an agro-economic water scarcity indicator, the water shadow price (WSP).

5.4.1 Water shadow price

The WSP is an outcome of the coupling of a biophysical vegetation model and an economic land use model and links spatially explicit water availability with economic conditions and driving forces in the land use and agricultural sector. Hence, the WSP considers explicitly the economics of water demand in an optimization approach, which has been consistently neglected by previous indicators (Sauer et al., 2010). It takes important economic drivers, like income, trade, production costs, and productivity growth into account which are crucial for assessing water scarcity. In general, the WSP provides a more comprehensive picture of water scarcity than purely biophysically based indicators.

On the other hand, the WSP has certain limitations to serve as an agro-economic water scarcity indicator. First of all, it is based on blue water, neglecting the interactions and influences of green water on the agricultural system. Those are especially important in the livestock sector, where the differences of green and blue water use are large (Hoekstra and Chapagain, 2007), comparing, for instance, extensive beef production on grasslands (mainly green water) with industrial livestock farming (partially fed with imported irrigated feed crops). Hence, more detailed water-related studies with a focus on the future development of livestock systems are needed. Further limitations are related to the MAgPIE model since the shadow price itself is directly linked to the overall goal function of minimizing production costs. Important shortcomings of the model are missing direct production distortions, like tariffs and subsidies as well as the consideration of only interregional but no international transport costs. Whereas those limitations reduce the WSP, several others increase it. One is demand in MAgPIE, which is exogenously given by the demand regressions (described in Appendix 3). This implies that price elasticities of demand are zero, i.e. consumption cannot be adjusted endogenously due to changing prices. Another limitation is irrigation efficiency. Though it is a dynamic input dependent on economic development, it cannot be changed endogenously by investments in the model. This may lower efficiency levels in the future, although the study by Sauer et al. (2010) reveals rather low rates due to investments. In general, the explained shortcomings are expected to influence the WSP but do not change it by an amount that we can estimate at this point.

Before calculating the WSP, the amount of available irrigation water in MAgPIE is derived from water discharge (from LPJmL) reduced by an irrigation efficiency parameter. In most studies irrigation efficiency is a static input or changes only due to exogenous scenarios (i.e. Fischer et al. (2007)). An exception is the approach by Sauer et al. (2010), in which the model decides to invest endogenously in a better irrigation system (step-wise improvement) based on population growth. In contrast to this approach, we have implemented irrigation efficiency as a dynamic input depending on the level of economic development (GDP per capita). Although income does not explain the whole variation, we demonstrate with our regression that it is a strongly correlated driver for efficiency improvement (also confirmed by Sauer et al. (2010) and Calzadilla et al. (011a)). Our irrigation efficiencies increase between 2 and 12 percentage points from 2005 to 2045. Fischer et al. (2007) assumes exogenous increases in efficiency of 10% per decade, whereas Sauer et al. (2010) is more in line with our rather moderate estimates.

5.4.2 Scenario assessment and uncertainty

The most general finding of our scenario analysis is that water scarcity in all regions increases until 2050, some with low rates like Sub-Saharan Africa and Latin America and others with high rates, like South Asia and the Middle East/North Africa region. Although no other study has examined such an agro-economic water scarcity at high spatial resolution, we can at least compare our results with studies displaying regional values. Rosegrant et al. (2002) project water scarcity levels with the IMPACT-WATER model up to 2025 and show generally moderate increases. For developed countries water scarcity actually decreases. Similar strong increases as in our study are found for North Africa, Middle East, China, and India. In contrast to our findings, they also project high increases in Latin America.

With more trade liberalisation, simulations indicate that the re-allocation of agricultural land use in the long run can help to reduce regional water scarcity, especially in world regions where water will become extremely scarce over the coming decades. The only exceptions to this rule are Australia, Japan and parts of Central Asia (mainly Kazakhstan), where water becomes a bit scarcer. Other trade studies, like the CGE (computable general equilibrium) analysis by Berrittella et al. (2008), found rather small effects (changes in water use below 10%). In contrast to our results, trade liberalisation leads to higher water use in USA and China and lower water use in Japan, whereas the remaining regions encounter similar trends. However, since the study looks only on the period 1997 till 2010, the comparability is limited. The same model, GTAP-W, is used by Calzadilla et al. (011b) for analyzing trade liberalisation scenarios until 2050. As in our case, Australia has the highest increase in water scarcity due to liberalisation, whereas South-East Asia, South Asia, Middle East, and Former Soviet Union benefit from lower pressure on water resources. Simulations by the WATERSIM model confirm that increased trade between water-abundant regions and water-scarce regions avoids further stress on water scarcity levels (de Fraiture et al., 2009). However, the comparison with our simulations has to be interpreted with caution since they assume perfect free trade, which is much more optimistic compared to our rather moderate scenarios.

International trade flows are mainly driven by economic forces. If appropriate regional water prices would serve as realistic indicators for water scarcity, this would be reflected in the economic calculations of producers and traders. A well-functioning trading system also serves as a kind of insurance scheme against production risks, because it is rather unlikely that huge harvest losses due to floods or droughts would occur simultaneously on a global scale in several important production regions (Fraser and Rimas, 2010). This function could become even more important under future conditions of severe climatic change. On the other hand, the chances for beneficial trade liberalisation, which relaxes the pressure on regional water scarcity levels, in the short to medium term should not be overestimated. International agricultural trade is heavily dominated by political preferences and influences, which are rarely concerned with resource use efficiency and which change only slowly over time. Poor, water-scarce countries also face the problem that increased imports of water-intensive goods or "virtual water" would have to be financed with foreign exchange (Seckler et al., 2000). This would require the development of competitive export sectors, which many developing countries, especially in Africa, failed to achieve in the past.

The second policy we explored is a shift from a business-as-usual diet to a fair diet, which contains the same share of animal-based products for every world region. If this shift is simulated the pressure on water scarcity in all regions is reduced, as plant-based calories contain less water in its production than animal-based calories. This is an unexpected outcome since the livestock share in some regions, for instance in SAS and MEA, increases in the fair diet scenario. The reason behind the lower water shadow prices (WSP) is the linkage between regions through trade, which translates less animal-based consumption in the developed countries into lower pressure in water-scarce regions like India or the Middle East. As a consequence the effects on WSP in developing regions are highest in the combined scenario of trade liberalisation and diet shift, whereas in developed countries the diet shift effects largely outweigh the trade effects.

To our knowledge there is no other study which has quantified the effects of lower animal-based consumption in detail and with which we can compare our results directly. Yet, Gerten et al. (2011) found out that the likelihood for a country to be water-scarce would be reduced, particularly in African countries, if animal calories are halved. Renault and Wallender (2000) analyzed the percentage of additional water which is saved according to different scenarios until 2025. The scenario which replaces 50% of meat by vegetal products comes to savings of 23% of the additional water and the one which replaces 50% of animal products yields in 39% savings. Comparing this to our fair diet scenario (scenario 2) without any trade changes, we calculated savings of 40% until 2025 and 28% until 2050. (Liu and Savenije, 2008) found positive effects of lower meat consumption for China, but concluded that virtual water trade and improvement of rainfed agriculture are the more promising strategies. Other studies, examining livestock reducing scenarios, found positive effects on the reduction of greenhouse gas emissions (Popp et al., 2010; Stehfest et al., 2009) and the pressure on cropland (Wirsenius et al., 2010).

The MAgPIE model has the unique feature of generating technological change rates endogenously based on investments in agricultural research and development. Our analysis reveals a lower pressure on agricultural productivity due to the above mentioned policies. The average global annual rate of technological change in agriculture until 2045 is 0.9% in the reference scenario, compared to 0.6% in the trade scenario, 0.7% in the fair diet scenario and 0.5% in the combined scenario. At the regional level those effects are much higher for regions like MEA and SAS but also NAM. Hence, we can state that increased trade and a fair diet help not only to reduce water scarcity, but also lower the pressure for innovation in agriculture. Furthermore, the policy scenarios lead globally to lower cropland expansion. However, as shown in Schmitz et al. (2012), this differs on a regional level and trade liberalisation leads to further deforestation in tropical regions, like South America, with negative implications for greenhouse gas emissions. Expansion of area equipped for irrigation amounts to 14% until 2045, which is roughly in line with the study by Sauer et al. (2010), who estimate an increase of 14% of irrigation area until 2030. In this context we have to emphasize again that no impacts from climate change are considered in this study. Those impacts are mainly changing temperature and precipitation patterns, which have heterogeneous effects on the regional water balance. Especially in many developing regions, this implies further threats on water availability (Gerten et al., 2011; Rockström et al., 2009; Vörösmarty et al., 2000). A detailed study by Fischer et al. (2007) concluded that climate change causes globally up to 20% more irrigation until 2080, which is nearly as much as irrigation has to expand due to socio-economic drivers in this time span.

Our sensitivity analysis is focused on different population and GDP scenarios. Although we used extreme sensitivity scenarios the variations in results are rather moderate. Water scarce regions, like South Asia and the Middle East, are most affected but the ranking order is hardly affected by different demand projections. The study by Schmitz et al. (2012) conducted the sensitivity of MAgPIE regarding technological change and land expansion and found that results changed in the range of -10% and +16% in terms of emissions and production costs. However, since only a limited number of model parameters have been tested, a more comprehensive sensitivity analysis would be necessary to reveal the whole range of possibilities.

Overall, our analysis indicates that only one of the considered policy measures in this study is not enough to keep water scarcity at levels observed in 2005. Only by combining both policies, global water shadow prices in 2045 are in most regions below the values in 2005. This does not hold for China, Australia, Japan, and countries in Sub-Saharan Africa, where additional strategies have to be developed in order to keep the pressure on water resources at current levels. Examples, which could be picked up by subsequent studies, are options to increase irrigation efficiency, improvements in infrastructure, institutional reforms and also the issue of water pricing.

5.5 Conclusion and policy implications

In many regions of the world water is already today a scarce resource. Due to insufficient price signals this is not yet recognized in all its consequences by most social actors.

Many developing countries, which are heavily dependent on the agricultural sector and located in dry areas, are especially affected by water shortage. Those countries will also be strongly affected by climate change in the form of altered precipitation patterns, which could further exacerbate their situation in the future. Water shortage could lead to higher food prices with negative effects on regional food security.

Under exogenous scenarios of population and income growth, the MAgPIE model calculates food demand and allows for future projections of spatially explicit water shadow prices and regional technological change rates. As water scarcity is continuously increasing and reaches severe dimensions in particular regions, like South Asia, Middle East, and North Africa, trade liberalisation and policies to control livestock demand are promising measures to curtail water scarcity. Concerning required productivity increases, the pressure to innovate is particularly reduced in importing regions, which are at the same time the regions with water scarcity. In the case of further trade liberalisation, we found that it is less effective (in terms of reducing water scarcity) for developed countries than for developing countries. This is particularly important since developed countries are often hampering further liberalisation efforts. Lower animal-based consumption in developed countries does not only reduce the domestic pressure on water but also reduce to a large extent water scarcity in developing countries. However, as Ridoutt et al. (2011) points out, production of livestock-based goods is very diverse in terms of water consumption. Rather than condemning the whole animal sector, a focus on low-water input systems should be an alternative policy strategy in developed countries.

In order to reach sustainable water demand in 2045, in many developing regions it is even not enough to count on trade liberalisation and reduced livestock demand in developed countries. Other measures like investment in breeding of water-saving plants, the promotion of water-saving production systems or improved irrigation infrastructure are needed. Furthermore, clearer incentives for improved water management have to be institutionalized. In many regions, water is seriously under-valued and lacking defined property rights, especially in the agricultural sector. The discussion about water pricing has to be conducted on the regional level. The same holds for tradable user rights for irrigation water, which can provide a possible way towards a more appropriate valuation of scarce water resources.

6 Synthesis and policy implications

"You know, farming looks mighty easy when your plow is a pencil and you're a thousand miles from the corn field."

Dwight D. Eisenhower in his address at Bradley University (25.9.1956)

Land use modelling as a scientific discipline has emerged over the last two decades. Its evolution has been strongly correlated with the development of computing power and related capabilities. Before, future scenarios were mainly a mental exercise based on qualitative appraisals, experiences, and observations. With the possibility to formalize and solve relationships through equations, it became a mathematical exercise based on principles from established scientific areas (like physics, biology, or economics). However, those principles, related assumptions, and underlying data are not free from errors and biases, which might lead to large uncertainties in results. To reduce uncertainties in land use modelling, the community has to establish best-practice methods through the scientific process. With this doctoral thesis, I want to contribute to this development.

The overarching research question of this thesis is: "How do intensification, cropland expansion and trade interact within the agricultural system and what are resulting environmental externalities with regards to land, water and emissions?". I addressed this question with the global land use model MAgPIE ("Model of Agricultural Production and its Impact on the Environment") and enhanced the model with several methodological processes, like technological change, international trade, land expansion, and irrigation improvements. All these processes reflect drivers of future food supply. In the different papers (Chapter 2, 3, 4 and 5), I analysed and discussed their coherence within the agricultural and environmental system. In the following, the most important conclusions and policy implications are summarized and synthesized.

1) Agricultural investments in developing countries

The interplay between technological change and land expansion is a decisive procedure in terms of future food availability. In MAgPIE, these processes are implemented in an endogenous way. By comparing past rates of technological change (TC) with modelled rates we found a good agreement (Figure 2.5). For the future, MAgPIE has projected highest TC rates in the Middle East and North Africa region as well as in South India and China. By protecting precious forests, like the tropical rainforest, required rates of technological progress have to increase considerably in Sub-Sahara Africa, Latin America, and Pacific Asia. Hence, in order to protect the environment and to meet the growing agricultural demand, it seems indispensable to boost investments in R&D and infrastructure. Hereby, the international focus of technological change in agriculture should lay on developing countries because of three arguments.

First, as my analysis demonstrates, costs for increasing agricultural yields are considerable lower in those countries than in developed countries with high yields already (Section 2.3). One reason is that important crops for developing countries, like millet, cassava, yam, and beans have gotten comparably little attention by scientists and breeders, especially in private organisations. As a result, the potential for higher yields of these crops through breeding is large (Huang et al., 2002). Another reason is the yield gap between actually achieved yields and potential maximum yields. In developing countries this yield gap is much larger than in developed countries (Rockström et al., 2007), which is mainly caused by a lack of investments in inputs, inefficient cultivation methods and an insufficient level of education. In order to combat these factors, domestic but also foreign investments in the agricultural sector are necessary.

Second, research has demonstrated that investments in the agricultural sector have by far the largest effect on poverty reduction in Africa and Asia (Thirtle et al., 2003). The general perception that economic development in Sub-Sahara Africa can be achieved through leapfrogging of agricultural and rural development has been proven wrong and has considerably contributed to an increase in poverty in the past two decades (de Janvry and Sadoulet, 2010).

Third, as shown in my analyses, investments in the agricultural sector reduce the pressure on land and the environment significantly (Section 2.3.2, 3.3.3, 4.3.2 and 5.3.2). Those investments have to be targeted well in order to achieve environmental protection goals. For instance, since most of the tropical rainforest is native to poor developing countries, it is essential to improve the yield level in those countries. Otherwise, forests will be cut back to secure the livelihood and generate income. However, Angelsen (2010) points out that local yield increases may encourage local deforestation due to higher profitability. As a solution, agriculture in low-forest areas of the country should be supported and at the same time, the livelihood of the local population close to the forests has to be secured in a sustainable way.

Although the importance and urgency of investments in the agricultural sector have been proposed extensively (Pardey and Beintema, 2001; Pardey et al., 2006; Alston et al., 2009), the transfer into practise is lacking behind, especially in Sub-Sahara Africa. Besides lower foreign development assistance for agriculture, domestic support for agriculture has also declined until the year 2000 (de Janvry and Sadoulet, 2010). In 2003, African heads of state promised to raise the budget for agriculture to 10% of total government spending by 2008 (Maputo Declaration, 2003). Although, agricultural spending has generally increased since then, the target was only met by 8 out of 38 countries (Fan et al., 2009). The low commitment to agriculture in Africa remains one of the main differences to Asia, where the Green Revolution was fuelled by high investments in the agricultural sector. In addition, higher attention of private companies for agriculture in developing countries is needed in order to meet the required productivity growth in the coming decades.

2) Environmental implications of trade liberalisation

The degree of trade liberalisation determines the amount of food which is produced at places where it is more efficient but not consumed. This is important, especially when resources, like land or water, are scarce at one place but abundant at other places. Through commodity trade, production inputs are traded virtually which might lead to reduced scarcity of resources. However, trade follows largely economic rationality, which means food is produced where it is cheapest under existing economic and political conditions. If scarce resources do not have a price (like water in many places) or its usage involves lower costs than its value for society (like the rainforest), increased trade might even worsen resource scarcity.

In the presented analyses I draw a heterogeneous picture of trade liberalisation. First, while increased trade leads to more deforestation and greenhouse gases in Latin America, it leads to the opposite in Pacific Asia (Section 4.3.1). Second, increased trade liberalisation causes, on the one hand, exacerbated water scarcity in South Australia, Japan, and Central Asia but on the other hand, less water scarcity in South Asia, Europe, China, and the United States (Section 5.3.1). Third, trade liberalisation reduces the pressure on agriculture. In most regions, especially in the Middle East and North Africa, required rates of technological change are considerably reduced due to higher imports (Section 3.3.3). Overall, results imply that future trade liberalisation efforts have to go in line with environmental regulations to prevent unsustainable resource exploitation.

The implementation of these kinds of regulations is challenging, since they might contradict with economic targets of developing countries and interests of powerful lobby groups. Nonetheless, as most environmental threats are caused through international linkages, developed countries have to face their responsibilities and to support those countries. As an example, I presented the case of deforestation in Latin America, where deforestation is likely to be accelerated due to higher foreign demand. The most effective policy would be to internalize the costs for generated externalities through market rationalities. If we just take carbon release from deforestation (leaving out other externalities) and include it in a possible global market for climate mitigation, deforestation would end after 2020 with assumed carbon prices of 15-20 US$/ton CO_2 (Section 4.4). Local policies, like direct regulations, or bilateral agreements, like transfer payments, are less effective due to leakage effects and higher transaction costs. Although, the design of such policies involve the overcoming of several international obstacles (see Section 4.5), there is no alternative to use the benefits of trade liberalisation and simultaneously prevent negative implications for the environment. Another example is the consumption of animal products in the developed world, which increases demand for land, water, and nutrients worldwide. By reducing consumption, the pressure on resources in developing countries could be diminished significantly.

3) Localisation of water scarcity

On a global average, blue water scarcity will intensify over the coming decades. However, as water scarcity is a local phenomenon with huge heterogeneity over the globe and within regions, more detailed information is needed. The presented agro-economic water scarcity indicator generated with MAgPIE (Section 5.3.1) gives a much more precise picture of water scarcity and its local dimension than most existing indicators. In many regions of the world, like large parts of South America, Sub-Sahara Africa, Russia, Pacific Asia and many smaller regions, water is abundant at present and will not get scarce in the future. In contrast, other regions like South Asia, the Middle East, North Africa, and South Australia are already threatened by dramatic water shortages and it is very likely that it will worsen in the future. In contrast to emissions of greenhouse gases, water scarcity has foremost local effects but the causes of it are partly triggered due to foreign demand. Australia, for instance, is one of the leading exporting countries of grains, which involves a lot of irrigation water. Another example are importing regions, like the Middle East and South Asia, which have to produce more food domestically (with negative implications on water resources) due to export restrictions of leading exporting nations. As a consequence, policies to combat water scarcity are not only a domestic affair but also an international responsibility.

Nonetheless, most effective policies should be related to direct savings of water since only a small portion of the available water reaches the plant effectively. A lot of water is not used for irrigation as a result of institutional failure or dilapidated infrastructure. Over 50% of water which is intended for irrigation is lost due to poor management, losses in the conveyance system and inefficient application to the plant (Rohwer et al., 2007). Improving this would have a direct effect on the level of water scarcity and agricultural productivity. On international level, trade plays an important role as a facilitator of virtual water trade, as illustrated above. In addition, reduced demand through lower consumption of animal products in the developed world would have a significant influence in almost all regions with water scarcity.

4) Uncertainty in land use modelling

Land use modelling is subject to huge uncertainties due to its large amount of data input and its aim to replicate complex relations. According to Funtowicz and Ravetz (1990) and Rotmans and van Asselt (2001), three types of uncertainties can be distinguished. First, technical uncertainties are related to quality and reliability of data used in the model. These arise through deficient preparation of data (temporal and spatial aggregation), data gaps and simplifications. Second, methodological uncertainties refer to a lack of knowledge about the right methods for analysing the data. Causal relationships are sometimes not understood entirely or appropriate methods are not known. Finally, epistemological uncertainties reflect the variability of reality related to, for instance, human behaviour, randomness of nature and society, and technological surprises.

Uncertainty analysis in land use modelling is not very widespread up to now. In this thesis, I make a first attempt to give an indication about uncertainty in MAgPIE and hereby, concentrate on technical and methodological uncertainties. I used input validation methods to test the quality of input data. Additionally, sensitivity and scenario analyses are applied to examine the uncertainty of outputs related to specific parameters and processes. Concerning input data, we rely partly on semi-measured or observed data. For instance, MAgPIE depends to a large extent on FAO statistics, which have the advantage to have a broad and consistent coverage of countries, commodities, and years. Unfortunately, data are only partly directly measured. Many countries do not report any data or they are flawed (Smil, 2000). The remaining gaps are mostly filled by expert assessment. Besides semi-measured data, modelled data (e.g. LPJmL) are used as input. Since those data are themselves subject to uncertainty, they have to be validated with other sources. As an example of input validation, I take the MAgPIE input for water withdrawal and availability. These data come from LPJmL and I compare these to the water withdrawal and availability data from the H08 water model (Hanasaki et al., 2008a,b). The comparison gives insights into the quality of used input data (Section 5.2.2). As an alternative, MAgPIE could have been run with both inputs in order to assess the differences in output. This method is quite common when using the results of different climate models as inputs (e.g. in Lotze-Campen et al. (2012)).

Another common uncertainty method is a sensitivity analysis of single input parameters. In this thesis I tested important parameters like land expansion costs, transport costs, technological change costs and trade liberalisation (Section 3.3.7 and 4.3.3). Results indicate that for the first three parameters, variability in outputs is highest. All these parameters affect directly the interplay between intensification and extensification. Especially, the endogenous behaviour of land expansion and technological change needs special attention since a lack of data makes the underlying processes difficult to understand. More attention on these processes is required in future research.

Finally, I applied scenario analyses as a further way to detect uncertainty. Nine different population and income projections have been tested regarding the influence on important model parameters like technological change and water shadow prices (Section 5.4.2). Especially the results of water-scarce regions are subject to signficant variations depending on the population and income scenario. However, as with the sensitivity analyses of single input parameters, those variations do not change the general conclusions.

Overall, the performed uncertainty analyses are only first attempts and it requires much more to examine the whole spectrum of uncertainty in such a model. For models like MAgPIE, with many different input parameters and complex processes, it will be a huge but necessary effort. In general, future research has to focus its agenda more on uncertainty analyses. As a consequence, approved methods and tools from other scientific areas have to be adapted to the usage in land use modelling and the communication of uncertainty to the public has to become more transparent.

Appendix

1 Mathematical MAgPIE description

MAgPIE (Model of Agricultural Production and its Impact on the Environment) is a nonlinear recursive dynamic optimization model that links regional economic information with grid-based biophysical constraints simulated by the dynamic vegetation model LPJmL. A simulation run with the simulation period T can be described as a set

$$X = \{x_t \mid t \in T\} \subseteq \Omega \tag{1}$$

of solutions of a time depending minimization problem, i.e. for every timestep $t \in T$ the following constraint is fulfilled

$$\forall y \in \Omega : g_t(x_t) \leq g_t(y), \tag{2}$$

where the goal function for $t \in T$

$$g_t(x_t) = g(t, x_t, x_{(t-1)}, ..., x_1, P_t) \tag{3}$$

depends on the solutions of the previous time steps $x_{(t-1)}, ..., x_1$ and a set of time depending parameters P_t. We may interprete a MAgPIE simulation run $X = \{x_t \mid t \in T\} \subseteq \Omega$ as an element of the vector space $\Omega_T = \Omega \times T$.

Sets

The dimension of the domain Ω, on which for each timestep the minimization problem is defined, and of Ω_T depends on the following sets:

- $T = \{\text{time steps } t\}$: Simulation time steps, where t denotes the current time step, $t - 1$ the previous time step and so on. The first simulated time step is $t = 1$.

- $I = \{\text{world regions } i\}$: Economic world regions in MAgPIE.

- $J = \{\text{spatial cells } j\}$: Highest disaggregation level in MAgPIE.
- $K = \{\text{simulated products } k\}$: Union of vegetal products V and livestock products L $(K = V \cup L)$.
- $L = \{\text{simulated livestock products } l\}$: Products simulated within the livestock sector of MAgPIE.
- $V = \{\text{vegetal products } v\}$: Products simulated within the crop sector of MAgPIE.
- $W = \{\text{water supply types } w\}$: Currently two types are implemented: rainfed 'rf' and irrigation 'ir'
- $C = \{\text{crop rotation groups } c\}$: Groups of crops, which produce similar effects in terms of crop rotation.

To highlight the substance of our model equations with regard to the agricultural and economic contents, we split our variable x_t into

$$x_t = \left(x_t^{area} \in \Omega^{area}, x_t^{prod} \in \Omega^{prod}, x_t^{tc} \in \Omega^{tc}\right) \in \Omega, \tag{4}$$

where the respective domains can be identified as the following vector spaces

$$\Omega^{area} = \mathbb{R}^{|J|} \times \mathbb{R}^{|V|} \times \mathbb{R}^{|W|} \tag{5}$$

$$\Omega^{prod} = \mathbb{R}^{|J|} \times \mathbb{R}^{|L|} \tag{6}$$

$$\Omega^{tc} = \mathbb{R}^{|I|} \tag{7}$$

As a result, we may specify the dimension of the solution space for each timestep as $dim\Omega = |J| \cdot |V| \cdot |W| + |J| \cdot |L| + |I|$ and the dimension of $\Omega_T = \Omega \times T$ as $dim\Omega_T = |T| \cdot dim\Omega = |T| \cdot (|J| \cdot |V| \cdot |W| + |J| \cdot |L| + |I|)$.

In the following, variables and parameters are provided with subscripts to indicate the dimension of the respective subdomains. Subscripts written in quotes are single elements of a set. The order of subscripts in the variable, parameter and function definitions does not change. The names of variables and parameters are written as superscript.

Variables

Since MAgPIE is a recursive dynamic optimization model, all variables refer to a certain time step $t \in T$. In each optimization step, only the variables belonging to the current time step are free variables. For all previous time steps, values were fixed in earlier optimization steps. As we have seen above, we currently distinguish three variables $x_t^{area} \in \Omega^{area}$, $x_t^{prod} \in \Omega^{prod}$ and $x_t^{tc} \in \Omega^{tc}$ that can be described as follows:

- $x^{area}_{t,j,v,w}$: The total area of each vegetal production activity v for each water supply type w, each cell j and each time step t [ha]

- $x^{prod}_{t,j,l}$: The total production of each livestock product l, for each cell j at each time step t [ton dry matter]

- $x^{tc}_{t,i}$: The amount of yield growth triggered by investments in R&D [-]

Parameters

Besides variables, the model is fed with a set of parameters P_t. These parameters are computed exogenously and are in contrast to variables of previous time steps fully independent of any simulation output. Although most parameters are time independent, there exist also some parameters which are time dependent.

- $p^{yield}_{t,j,v,w}$: Yield potentials for each time step, each cell, each crop and each water supply type taking only natural variations into account and excluding changes due to technological change [ton/ha]

- $p^{dem}_{t,i,k}$: Regional food and material demand in each time step for each product [10^6 ton]

- $p^{fshr}_{i,l,k}$: Feed share describing the share of each product k of total feed production for livestock product l and corresponding transformation from GJ feed in ton dry matter [ton/GJ]

- $p^{feed}_{i,l}$: Feed requirements for each livestock product l in each region i [GJ/ton]

- $p^{byprod}_{i,k,l}$: Feed energy delivered by the byproducts of k that are avaiable as feedstock for the livestock product l [GJ/ton]

- $p^{frv}_{i,v}$: Area related factor requirements for each crop and each region. The parameter is the product of observed yields in 1995 (FAOSTAT, 2009) and the production costs shown in table 2.4 [US$/ha]

- $p^{frl}_{i,l}$: Production related factor requirements for livestock products for each livestock type and each region [US$/ton]

- p^{lcc}_{i}: Area related land conversion costs for each region [US$/ha]

- p^{tcc}: Technological change costs factor containing an interest correction, an expected lifetime factor and a general cost factor [US$/ha]

- $p^{\tau 1}_{i,v}$: τ-Factor representing the agricultural land use intensity in the first simulation time step for each crop in each region [-]

- p^{cxp}: Correlation Exponent between τ-Factor and technological change costs [-]

- $p_{i,v}^{seed}$: Share of production that is used as seed for the next period calculated for each crop in each region [-]
- $p_{t,i,k}^{xs}$: Regional excess supply for each product and each time step describing the amount produced for export [10^6 ton]
- $p_{i,k}^{sf}$: Regional self sufficiencies for each product [-]
- p^{tb}: Trade balance reduction factor. This factor is always less or equal 1 and is used to relax the trade balance constraints depending on the particular trade scenario.
- p_j^{land}: Total amount of land available for crop production in each cell [10^6 ha]
- $p_j^{ir.land}$: Total amount of land equipped for irrigation in each cell [10^6 ha]
- $p_{j,k}^{watreq}$: Cellular water requirements for each product [$m^3/ton/a$]
- p_j^{water}: Amount of water available for production in each cell [m^3/a]
- p_c^{rmax}: Maximum share of crop groups in relation to total agricultural area [-]
- p_c^{rmin}: Minimum share of crop groups in relation to total agricultural area [-]

[all ton units in dry matter]

Sub-functions

To lighten the general model structure, some model components which appear more than once in the model description and depend on the variables of the current time step t are arranged as functions:

$$f_{t,i}^{growth}(x_t) = \prod_{\tau=1}^{t} (1 + x_{\tau,i}^{tc}) \tag{8}$$

$$f_{t,i,k}^{prod}(x_t) = \sum_{j_i} \begin{cases} x_{t,j,k}^{prod} & : k \in L \\ \sum_w x_{t,j,k,w}^{area} p_{t,j,k,w}^{yield} f_{t,i}^{growth}(x_t) & : k \in V \end{cases} \tag{9}$$

$$f_{t,i,k}^{dem}(x_t) = p_{t,i,k}^{dem} + \sum_l p_{i,l,k}^{fshr} \left(p_{i,l}^{feed} f_{t,i,l}^{prod}(x_t) - \sum_\kappa p_{i,\kappa,l}^{byprod} f_{t,i,\kappa}^{prod}(x_t) \right). \tag{10}$$

- $f_{t,i}^{growth}$: Growth function describing the aggregated yield amplification due to technological change compared to the level in the starting year for each year t and region i.

- $f^{prod}_{t,i,k}$: Function representing the total regional production of a product k in region i at timestep t. In the case of vegetal products, it is derived by multiplying the current yield level with the total area used to produce this product. In the case of livestock products, it is represented by the related production variable.

- $f^{dem}_{t,i,k}$: Function defining the demand for product k in region i at timestep t. It consists of an exogenous demand for food and materials $p^{dem}_{t,i,k}$ and an endogenous demand for feed, which is calculated as the feed demand generated by the livestock production minus the feed supply gained through byproducts.

Goal function

$$g_t(x_t) = g(t, x_t, x_{(t-1)}, ..., x_1, P_t) \tag{11}$$

The goal function describes the value that is minimized in our recursive dynamic optimization model structure in each timestep. It is time dependent, i.e it differs for each time step, depending on the solutions of the previous time steps. We define the goal function as follows (with $\Theta(x)$ as Heaviside step function):

$$\begin{aligned} g_t(x_t) = & \sum_{i,v} \left(p^{frv}_{i,v} f^{growth}_{t,i}(x_t) \sum_{j_i,w} x^{area}_{t,j,v,w} \right) \\ & + \sum_{i,l} \left(p^{frl}_{i,l} f^{prod}_{t,i,l}(x_t) \right) \\ & + \sum_{i} \left(p^{lcc}_{i} \sum_{j_i,v,w} \left(x^{area}_{t,j,v,w} - x^{area}_{t-1,j,v,w} \right) \Theta \left(x^{area}_{t,j,v,w} - x^{area}_{t-1,j,v,w} \right) \right) \\ & + p^{tcc} \sum_{i} \left(x^{tc}_{t,i} \left(\frac{1}{|V|} \sum_{v} p^{\tau 1}_{i,v} f^{growth}_{t,i}(x_t) \right)^{p^{cxp}} \sum_{j_i,v,w} x^{area}_{t-1,j,v,w} \right). \end{aligned} \tag{12}$$

The function describes the total costs of agricultural production. The total costs can be splitted in four terms: 1. The area depending factor costs of vegetal production, which increase with the yield gain due to technological development. 2. The factor costs of livestock production depending on the production output. 3. The land conversion costs which arise, when non-agricultural land is cleared and prepared for agricultural production. 4. The costs, which arise by investing in technological development to increase yields by new inventions and improvements in management strategies. The technological change costs are proportional to the total cropland area of a region and increase disproportionate with the yield growth bought in the current timestep and the agricultural land-use intensity.

Constraints

Constraints are used to describe the boundary conditions, under which the goal function is minimized.

Global demand constraints (for each activity k)

$$\sum_i \frac{f^{prod}_{t,i,k}(x_t)}{1+p^{seed}_{i,k}} \geq \sum_i f^{dem}_{t,i,k}(x_t) \tag{13}$$

These constraints describe the global demand for agricultural commodities: The total production of a commodity k adjusted by the seed share required for the next production iteration has to meet the demand for this product.

Tradebalance (for each region i and product k)

$$\frac{f^{prod}_{t,i,k}(x_t)}{1+p^{seed}_{i,k}} \geq p^{tb} \begin{cases} f^{dem}_{t,i,k}(x_t) + p^{xs}_{t,i,k} & : p^{sf}_{i,k} \geq 1 \\ f^{dem}_{t,i,k}(x_t) p^{sf}_{i,k} & : p^{sf}_{i,k} < 1 \end{cases} \tag{14}$$

The trade balance constraints are similar to the global demand constraints, except that it acts on a regional level. In the case of an exporting region (self sufficiency for the product k is greater than 1), the production has to meet the domestic demand supplemented by the demand caused due to export. In the case of importing regions (self sufficiency less than 1), the domestic demand is multiplied with the self sufficiency to describe the amount which has to be produced by the region itself. In both cases the demand is multiplied with a so called "trade balance reduction factor". This factor is always less or equal 1 and is used to relax the trade balance constraints depending on the particular trade scenario, that is run.

Land constraint (for each cell j)

$$\sum_{v,w} x^{area}_{t,j,v,w} \leq p^{land}_j \tag{15}$$

$$\sum_{v} x^{area}_{t,j,v,'ir'} \leq p^{ir.land}_j \tag{16}$$

The land constraints guarantee, that no more land is used for production than available. The first set of land constraints ensures the land availability for agricultural production in general. The second one secures, that irrigated crop production is restricted to areas that are equipped for irrigation.

Water constraints (for each cell j)

$$\sum_v x^{area}_{t,j,v,'ir'} p^{yield}_{t,j,v,'ir'} f^{growth}_{t,i(j)}(x_t) p^{watreq}_{j,v} + \sum_l x^{prod}_{t,j,l} p^{watreq}_{j,l} \leq p^{water}_j \tag{17}$$

In MAgPIE, the production of animal commodities as well as vegetal goods produced with irrigation requires water. The required amount of water is proportional to the production volumne. The whole cellular water demand must be less or equal to the water available for production in this cell.

Rotational constraints (for each crop rotation group c, cell j and irrigation type w)

$$\sum_{v_c} x^{area}_{t,j,v,w} \leq p^{rmax}_c \sum_{v} x^{area}_{t,j,v,w} \tag{18}$$

$$\sum_{v_c} x^{area}_{t,j,v,w} \geq p^{rmin}_c \sum_{v} x^{area}_{t,j,v,w} \tag{19}$$

The rotational constraints are used to describe crop rotations, but also other aspects such as cultural preferences or efforts of autonome food production systems. This is achieved by defining for each vegetal product a maximum and minimum share relative to total area under production in a cell. While crop rotation structures are exclusively described with the maximum share constraints, cultural preferences and autonomy efforts are basically described with the minimum constraints.

2 Specific MAgPIE description

Regions and products in MAgPIE

The regional disaggregation of MAgPIE is illustrated in Figure1 with the abbreviations in Table 1.

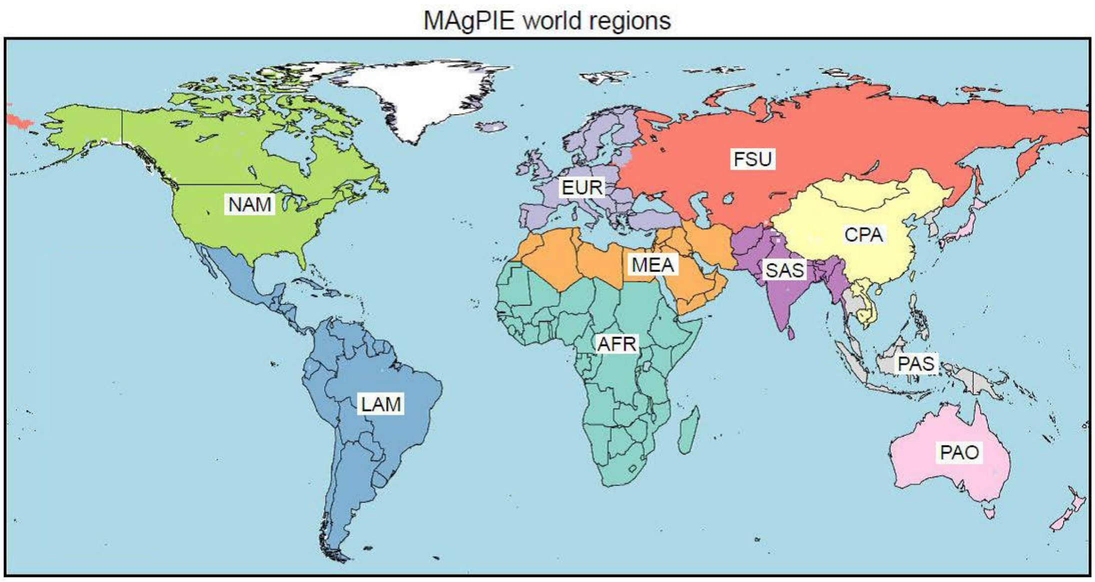


Figure 1: MAgPIE regional world map

MAgPIE distinguishes 16 different cropping activities and 5 livestock activities (Table 2).

Table 1: World regions in MAgPIE

Abbreviation	Regions
AFR	Sub-Sahara Africa
CPA	Centrally Planned Asia (incl. China)
EUR	Europe (incl. Turkey)
FSU	Former Soviet Union
LAM	Latin America
MEA	Middle East and North Africa
NAM	North America
PAO	Pacific OECD (Australia, Japan and New Zealand)
PAS	Pacific Asia
SAS	South Asia (incl. India)

Table 2: Cropping and livestock activities in MAgPIE

Cropping Activities		Livestock Activities
temperate cereals	oil palm	ruminant meat
maize	pulses	pig meat
tropical cereals	potato	poultry meat
rice	cassava	eggs
soybean	sugar beet	milk
rapeseed	sugar cane	
groundnut	cotton	
sunflower	others	

Specific implementation characteristics of technological change

For the implementation of technological change in MAgPIE some characteristics of the model and the agricultural sector have to be considered: Typically, for endogenous technology implementations in economic models an intertemporal optimisation approach is used due to the need of some kind of planning foresight (Ma and Nakamori, 2009). In contrast, MAgPIE is a recursive dynamic optimisation model which solves each time step separately. To be able to reproduce planning foresight in MAgPIE we use the annuity approach to transfer lump-sum TC investment to periodic payments including interest (Kellison, 1991). Investment decisions are taken by the model under the assumption of a 20-year lifetime of TC yield gains.

Another issue is the implementation of a 15-year lag between R&D investment and yield impact. The model decides, based on the expectations for 15 years later, how much should be invested. However, since there is no other cross-connection between these time steps, it is possible to shift the investments to the time step when its impact takes place. This means: if the model needs yield growth in the year 2025 due to higher demand expectations, these 2025 model investments must have been made in 2010. However, the costs for R&D in 2010 in the model will be compounded and paid in 2025. This implementation allows for endogenising technological change in a land use model without using intertemporal optimisation.

A non-intertemporal implementation has the advantage of reproducing the observed effect of continuous underinvestment in agricultural R&D (Ruttan, 1980; Roseboom, 2002). This market failure is caused by the limited foresight of decision makers concerning investments in R&D (Slaughter, 1996). An intertemporal optimisation model, however, would anticipate all the future benefits of R&D investments, which would lead to an optimal R&D investment path in R&D and an overestimation of yield increases, compared with observed trends.

3 Input data

Projected demand

year	AFR	CPA	EUR	FSU	LAM	MEA	NAM	PAO	PAS	SAS
I. Cereals										
2005	128	535	279	128	188	139	248	52	156	322
2015	180	665	302	145	253	180	278	58	196	397
2025	239	795	321	154	322	222	305	64	239	476
2035	300	915	335	155	380	260	328	70	288	550
2045	360	1036	340	155	422	291	347	74	338	622
II. Oilcrops										
2005	23	53	29	5	33	13	48	8	24	29
2015	31	63	31	6	40	17	55	9	31	34
2025	40	73	33	6	47	20	63	9	39	39
2035	50	82	34	7	54	24	70	10	49	44
2045	61	91	35	7	61	27	77	10	59	48
III. Starch Plants										
2005	65	65	25	12	19	3	7	2	12	9
2015	85	78	27	13	24	4	8	2	16	12
2025	109	88	29	13	28	5	10	3	20	14
2035	134	94	30	13	31	6	12	3	24	16
2045	159	95	31	12	33	6	14	3	29	19
IV. Sugar Crops										
2005	22	34	40	20	128	26	50	9	32	97
2015	28	37	42	21	152	31	54	9	37	112
2025	36	40	44	21	176	37	59	10	42	126
2035	43	40	45	21	198	42	63	10	46	136
2045	50	40	45	20	219	47	67	10	50	145
V. Sugar Crops										
2005	5	34	22	6	15	4	18	4	5	5
2015	6	44	24	8	20	5	21	4	7	8
2025	9	53	26	10	24	7	23	5	9	11
2035	12	61	27	10	28	8	26	5	11	13
2045	16	67	28	12	33	10	29	5	14	16

Table 3: Demand for cereals (I), oilcrops (II), starch plants (III), sugar crops (IV) and meat (V) for the ten world regions from 2005 to 2045 (in mio t.)

Demand sensitivity

In MAgPIE, demand for agricultural products is fixed for every region and every time step and cannot be influenced by the optimization process. Future trends in food demand are computed as a function of income (measured in terms of Gross Domestic Product (GDP)) per capita based on a cross-country regression. The underlining GDP scenarios are calculated by following the methodology proposed by Hawksworth (2006), who model the output with a Cobb-Douglas production function based on investment data from Heston et al. (2011). We combine the GDP output scenarios with the three different UN population scenarios to get, in total, nine different GDP per capita scenarios (Table 4), which result in nine different scenarios for food demand. The scenario with the label E is taken as the default scenario in our study, whereas the other eight scenarios are used for the sensitivity analysis.

For the calculation of food demand we use the relation between total calories C_T and income I_{MER} (measured in market exchange rate per capita). This relation is defined by a power function and estimated with a fixed effect model with time-dependent variables. Equation 20 shows the estimated function.

$$C_T = \exp(2.83 \cdot 10^{-3} + 2.13 \cdot 10^{-3} \cdot years) \cdot I_{MER}^{0.16 + -3.12 \cdot 10^{-5} \cdot years} \tag{20}$$

The results in 1995 were calibrated to food demand by FAO (FAOSTAT, 2010). Figure 2 illustrates the total consumption (in GJ) for the ten world regions in MAgPIE until 2045. In the figure it is differentiated between the business-as-usual diet scenario and the fair diet scenario, where livestock consumption converts to a maximum share of 20%. Highest total consumption is projected for SAS, CPA, and AFR. In CPA the growth rate stagnates after 2025 and the difference to the fair diet scenario is largest compared to the other regions.

The drivers for the share of livestock products in total caloric intake are income, population growth, and time. In order to calculate the animal calorie consumption, the share of animal based calories C_{AS} is estimated by equation 21.

$$C_{AS} = \exp(-36.73 + 4.5 \cdot \ln(I_{MER}) + 0.016 \cdot year - 0.0021 \cdot \ln(I_{MER}) \cdot year) \tag{21}$$

The results in 1995 were corrected by a constant share of fish products and calibrated to the livestock share by FAO (FAOSTAT, 2010). Figure 3 displays the resulting livestock consumption as share of total consumption. The livestock-consumption share in CPA increases most, whereas the share decreases in regions, like EUR or NAM. Applying the fair diet scenario all regions move continuously to around 19%, the exception is PAO, where the share of fish products is comparatively large and the rate is reduced to around 14%.

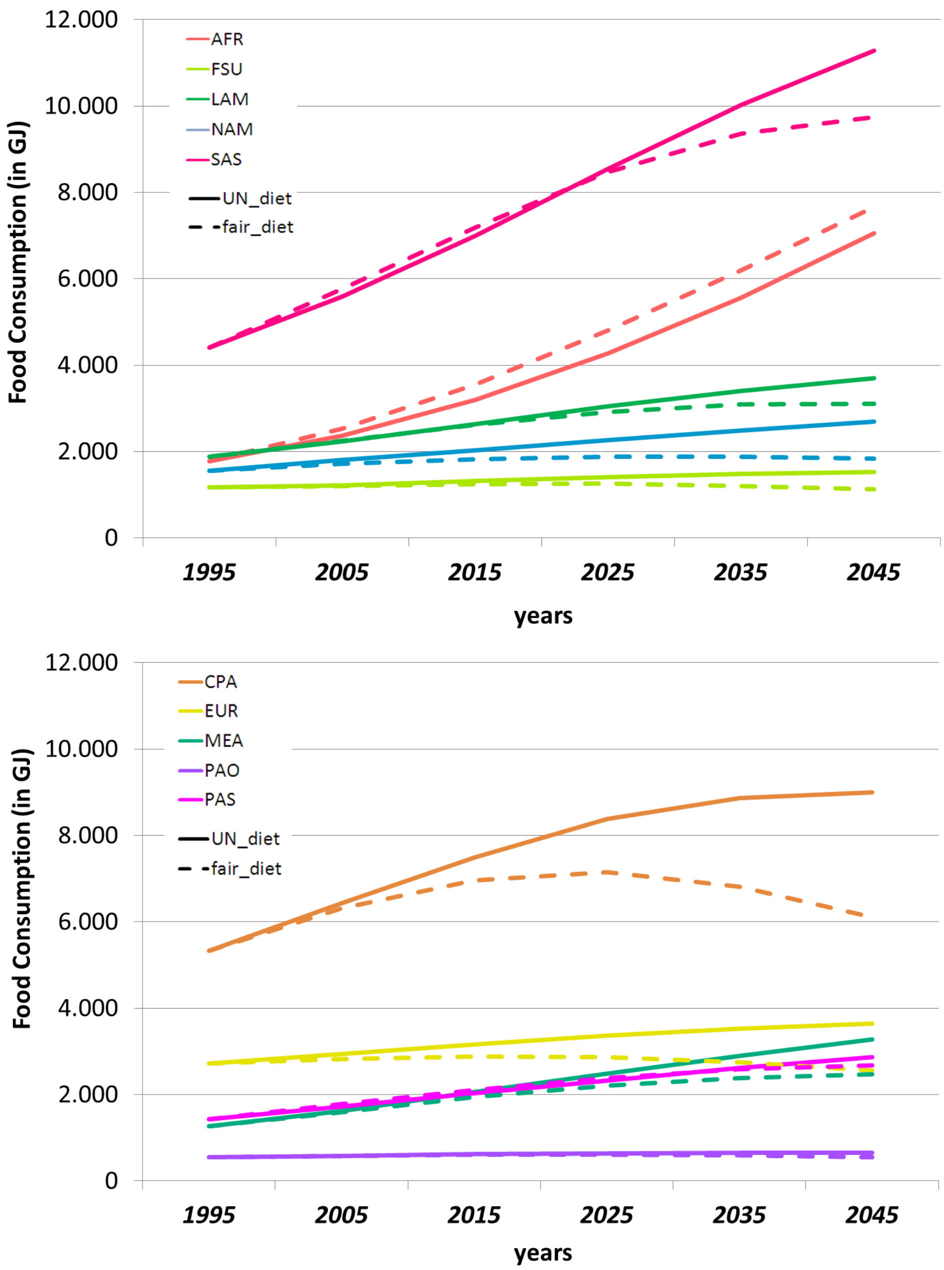


Figure 2: Food demand (in GJ) in the different world regions under the UN scenario (solid line) and the fair diet scenario (dashed line)

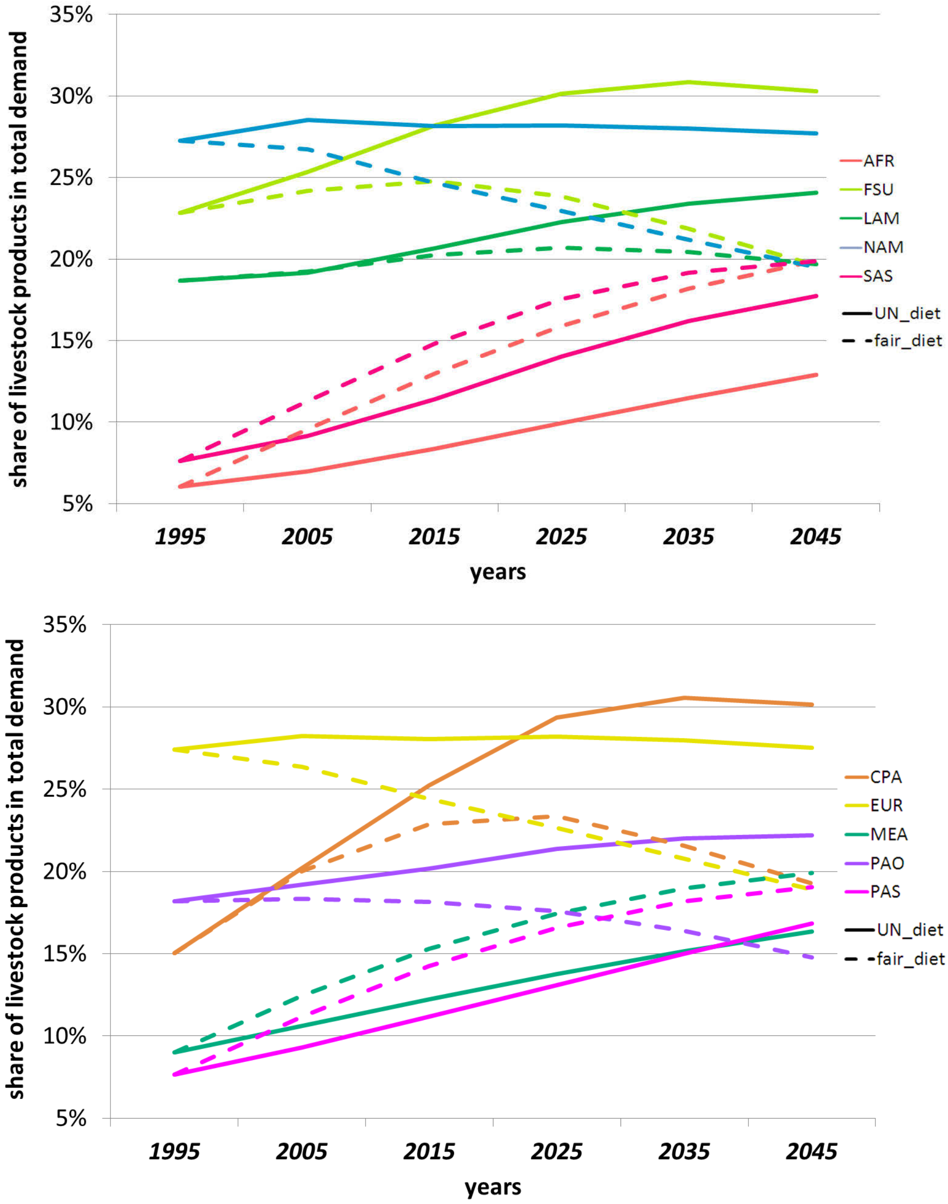


Figure 3: Livestock share of total demand in the different world regions under the UN scenario (solid line) and the fair diet scenario (dashed line)

Table 4: Composition of the nine population and GDP sensitivity scenarios

Label	UN Population	GDP Growth
A	low	slow
B	low	moderate
C	low	fast
D	medium	slow
$E(default)$	medium	moderate
F	medium	fast
G	high	slow
H	high	moderate
I	high	fast

Self sufficiency rates

Table 5 show the self sufficiency ratios for all regions and crop types obtained from the FAO database. The self sufficiency rates of heavily traded goods like cereals or oilseeds vary to a large extent among the regions. In contrast, crops like potato or cassava are mainly produced for domestic consumption and traded less [1].

region	tece	maize	trce	rice	soybean	rapeseed	groundn.	sunfl.
AFR	0,47	0,97	0,99	0,64	0,35	0,06	1,10	0,68
CPA	0,90	1,00	1,02	1,04	0,60	0,86	1,08	0,97
EUR	1,12	0,90	0,93	0,59	0,10	1,51	0,06	0,91
FSU	0,81	0,58	0,87	0,72	0,38	1,00	0,17	1,26
LAM	0,70	0,93	0,78	0,94	1,87	0,07	1,92	2,14
MEA	0,58	2,00	0,67	0,68	0,03	0,05	0,91	0,08
NAM	1,78	1,40	1,47	1,57	1,69	2,14	1,26	2,17
PAO	1,42	0,03	0,43	1,10	0,03	0,23	0,25	0,66
PAS	0,06	0,55	0,54	1,06	0,47	0,06	0,78	0,00
SAS	0,95	1,01	1,00	1,04	0,61	0,97	1,04	0,80

region	oilpalm	pulses	potato	cassava	scane	sbeet	cotton	others
AFR	0,96	0,96	0,98	1,00	8	1	1,09	1,06
CPA	0,15	1,23	1,02	0,99	0,88	0,89	0,98	1,01
EUR	0,00	0,85	1,01	0,01	0	1,38	0,92	0,91
FSU	0,00	1,07	0,99	0	0,00	0,75	1,02	0,88
LAM	0,86	0,97	0,96	1,01	1,38	1,40	1,05	1,36
MEA	0,00	0,78	1,00	0,89	0,29	0,49	0,53	0,99
NAM	0,00	1,99	1,07	0,68	0,20	0,95	1,26	0,84
PAO	0,00	1,89	0,88	0,71	1,32	1,32	0,87	0,78
PAS	3,36	0,78	0,82	1,71	1,13	1,00	0,44	1,17
SAS	0,00	0,98	1,00	1,01	1,06	1,06	1,05	1,01

Table 5: Self Sufficiency rates for the ten world regions in 1995 (FAOSTAT, 2010)

[1] Abbreviations for crop types: tece = temperate cereals, trce = tropical cereals, groundn = groundnuts, sunfl = sunflower, scane = sugar cane, sbeet = sugar beet

Export shares

Table 6 show the export share for the ten world regions and all crops in MAgPIE obtained from FAO data for the year 1995 (FAOSTAT, 2010).

region	tece	maize	trce	rice	soybean	rapeseed	groundn.	sunfl.	oilpalm	pulses	potato
AFR	-	-	-	-	-	-	0,23	-	-	-	-
CPA	-	0,01	0,03	0,34	-	-	0,33	-	-	0,23	0,34
EUR	0,30	-	-	-	-	0,47	-	-	-	-	0,16
FSU	-	-	-	-	-	-	-	0,22	-	0,07	-
LAM	-	-	-	-	0,41	-	0,17	0,57	-	-	-
MEA	-	-	-	-	-	-	-	-	-	-	-
NAM	0,61	0,99	0,96	0,12	0,59	0,53	0,15	0,21	-	0,43	0,50
PAO	0,09	-	-	0,06	-	-	-	-	-	0,27	-
PAS	-	-	-	0,23	-	-	-	-	1	-	-
SAS	-	-	0,01	0,25	-	-	0,12	-	-	-	-

region	cassava	sugarc.	sugarb.	others	cotton	ruminant	pig	chicken	egg	milk
AFR	0,03	-	-	0,08	0,07	0,12	0,01	0,02	0,02	0,07
CPA	-	-	-	0,04	-	0,33	0,65	0,21	0,53	0,09
EUR	-	-	0,96	-	-	-	0,14	0,13	0,06	0,17
FSU	-	-	-	-	0,03	-	-	0	0,02	-
LAM	0,02	0,79	0,02	0,60	0,05	0,23	0,03	0,25	0,10	0,07
MEA	-	-	-	-	-	-	-	0,05	0,04	0,01
NAM	-	-	-	-	0,68	0,08	0,11	0,24	0,08	0,05
PAO	-	0,05	0,02	-	-	0,16	-	-	-	0,19
PAS	0,95	0,07	-	0,25	-	-	0,05	0,05	0,06	-
SAS	-	0,09	-	0,03	0,17	0,08	0,01	0,05	0,09	0,35

Table 6: Export shares for the ten world regions in 1995 (FAOSTAT, 2010)

Irrigation efficiencies

Figure 4 shows the irrigation efficiencies as result of the cross-country regression with income per capita. The values are based on population and income data of the default scenario E.

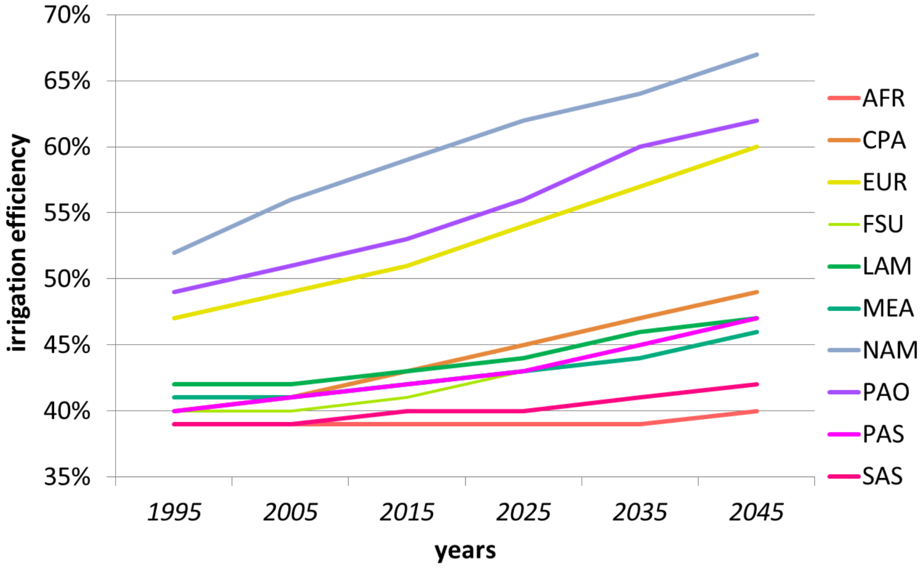


Figure 4: Irrigation efficiency in the ten aggregated world regions from 1995 to 2045 based on the cross-country regression

4 Further results

Netexport rates

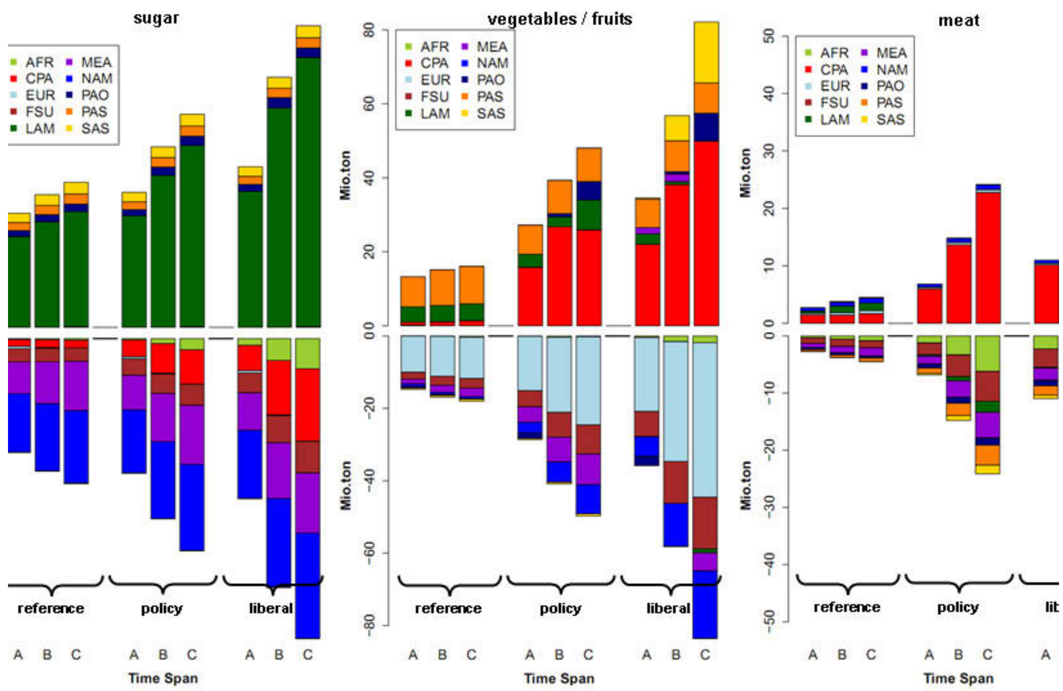


Figure 5: Net export quantities of sugar, vegetable/fruits and meat (ruminant and non-ruminant) for ten world regions in three trade scenarios and for three time spans (A = 2005-2020; B= 2020-2035; C= 2035-2050)

Non-CO_2 emissions

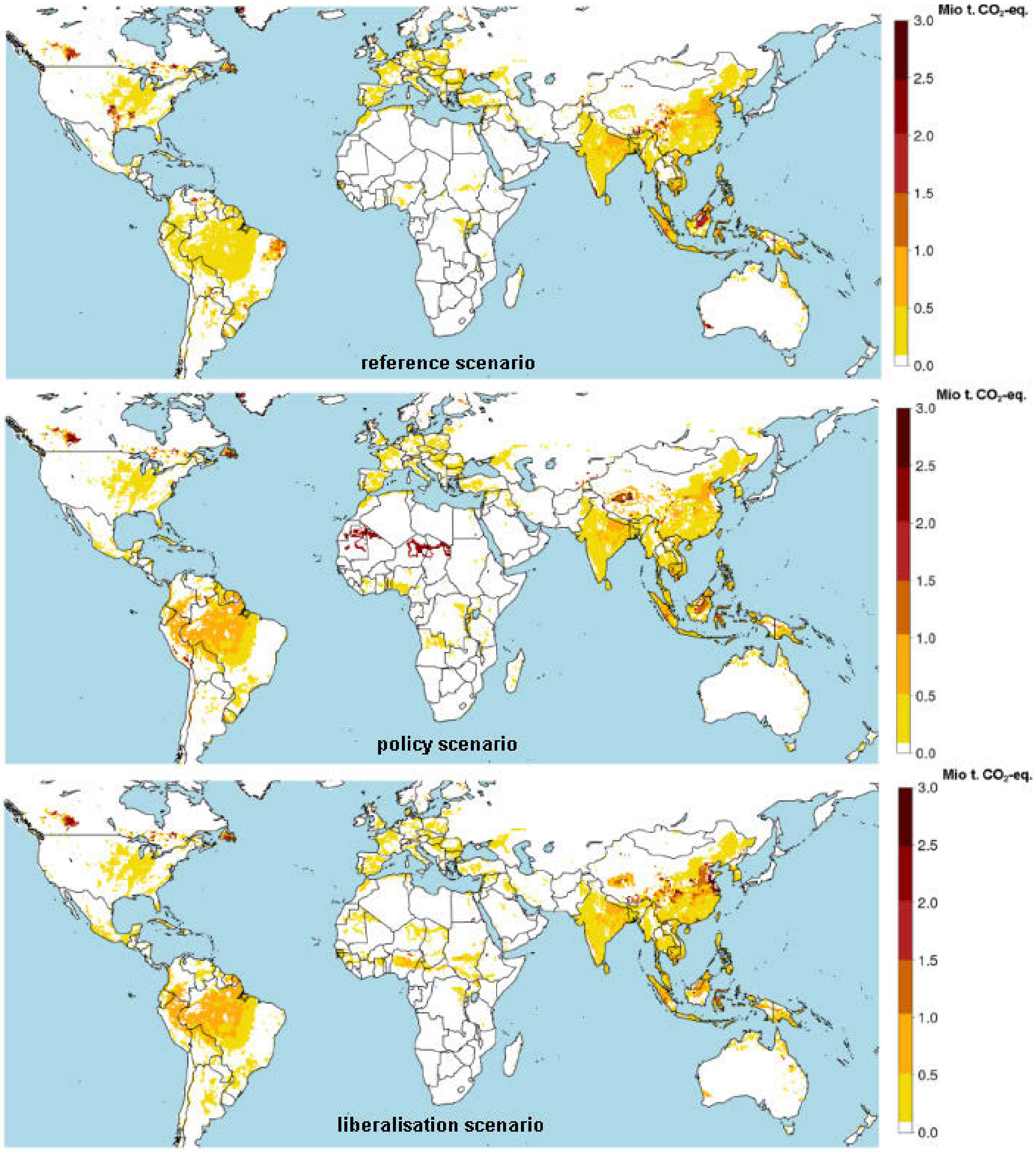


Figure 6: Mapping of annual non-CO_2 Emissions (average over 2005-2050) for the three trade scenarios

5 Sensitivity analysis

Land Expansion and Technological Change

(a) Land Expansion from 2005 to 2045

region	Standard model			cheapTC			expensiveTC			lowtrans			hightrans		
	refer	*pol*	*lib*	*refer*	*pol*	*lib*	*refer*	*pol*	*lib*	*refer*	*pol*	*lib*	*refer*	*pol*	*lib*
AFR	157,0	157,0	157,0	0%	0%	0%	0%	0%	0%	1%	1%	1%	0%	0%	0%
CPA	6,2	6,2	6,2	0%	0%	0%	0%	0%	0%	0%	0%	0%	-4%	-4%	-4%
EUR	0,0	0,0	0,0	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
FSU	5,1	3,9	4,0	0%	-100%	-100%	0%	1%	29%	0%	-100%	-1%	-1%	29%	28%
LAM	215,1	387,2	407,8	-5%	-37%	-30%	2%	5%	3%	5%	5%	6%	-19%	-19%	-19%
MEA	2,5	2,5	2,5	0%	0%	0%	0%	0%	0%	45%	45%	45%	-1%	-1%	-1%
NAM	40,3	40,3	40,3	0%	0%	0%	0%	0%	0%	-2%	-2%	-2%	3%	3%	3%
PAO	62,4	43,0	43,2	-5%	-4%	-4%	3%	78%	78%	1%	30%	71%	-14%	-4%	-15%
PAS	59,9	62,7	63,9	-9%	-12%	-8%	5%	5%	18%	18%	21%	24%	-28%	-29%	-38%
SAS	13,2	13,2	13,2	0%	0%	0%	0%	0%	0%	-2%	-2%	-2%	10%	10%	10%

(b) Annual Technological Change Rates from 2005 to 2045 (average)

region	Standard model			cheapTC			expensiveTC			lowtrans			hightrans		
	refer	*pol*	*lib*	*refer*	*pol*	*lib*	*refer*	*pol*	*lib*	*refer*	*pol*	*lib*	*refer*	*pol*	*lib*
AFR	1,4%	1,3%	1,3%	0pp	5pp	-2pp	0pp	-1pp	2pp	0pp	-5pp	-2pp	1pp	9pp	5pp
CPA	2,0%	1,9%	1,8%	1pp	13pp	20pp	0pp	-9pp	-12pp	0pp	-3pp	-4pp	1pp	3pp	5pp
EUR	1,0%	0,7%	0,6%	0pp	0pp	0pp	0pp	0pp	0pp	0pp	0pp	0pp	0pp	0pp	0pp
FSU	0,4%	0,0%	0,0%	-3pp	0pp	0pp	3pp	0pp	0pp	-3pp	0pp	0pp	0pp	0pp	0pp
LAM	0,5%	0,6%	0,7%	8pp	16pp	-3pp	-2pp	-5pp	3pp	-10pp	-6pp	-10pp	43pp	31pp	22pp
MEA	2,2%	1,0%	0,5%	0pp	1pp	-6pp	0pp	-6pp	-2pp	0pp	-2pp	-10pp	0pp	4pp	54pp
NAM	1,5%	1,4%	1,2%	1pp	1pp	-1pp	0pp	1pp	-1pp	0pp	0pp	-2pp	1pp	1pp	0pp
PAO	0,2%	0,2%	0,2%	25pp	0pp	-33pp	-19pp	-5pp	8pp	-31pp	-11pp	-21pp	75pp	21pp	0pp
PAS	0,7%	0,7%	0,7%	12pp	10pp	-6pp	-6pp	-1pp	4pp	-20pp	-18pp	-18pp	39pp	4pp	1pp
SAS	2,0%	1,6%	1,1%	0pp	0pp	6pp	0pp	0pp	-8pp	0pp	0pp	-6pp	0pp	0pp	6pp

Table 7: Land expansion and technological change rates in different world regions in the standard model version and differences in percentage points (pp) for the different sensitivity tests compared to respective standard model scenario.

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Scientific Publications

Peer-Reviewed Publications

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Selbständigkeitserklärung

Ich erkläre, dass ich die vorliegende Arbeit selbständig und nur unter Verwendung der angegebenen Literatur und Hilfsmittel angefertigt habe.

Berlin, den 1. Juni 2012 Christoph Schmitz